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Proceedings of the Third Annual Forest Inventory and Analysis Symposium

Traverse City, Michigan
October 17-19, 2001



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Proceedings of the Third Annual Forest Inventory and Analysis Symposium

Meeting jointly with the 35th Midwest Mensurationists' Meeting

Edited by
**Ronald E. McRoberts
Gregory A. Reams
Paul C. Van Deusen
John W. Moser**

**Traverse City, Michigan
October 17-19, 2001**

Sponsored by
**Forest Inventory Analysis Program USDA Forest Service
and
Midwest Forest Mensurationists**

PREFACE

The Third Annual Forest Inventory and Analysis Symposium was held jointly with the 35th midwest Forest Mensurationists' Meeting at Grand Traverse Lodge, Traverse City, Michigan, October 17-19, 2001. The Symposium series and the accompanying proceedings document research in support of annual forest inventories conducted under the auspices of the national Forest Inventory and Analysis (FIA) program of the USDA Forest Service. Research reported at the 2001 Symposium was in a variety of areas including statistical estimation and modeling, remote sensing and geographic information systems, information management, analysis, and the use of FIA data for an increasing number of purposes. The Symposium organizers thank all presenters and convey special thanks to those who submitted their papers for this publication,

Ronald E. McRoberts
Gregory A. Reams
Paul C. Van Deusen
John W. Moser
St. Paul, Minnesota

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PER TREE ESTIMATES WITH *N*-TREE DISTANCE SAMPLING: AN APPLICATION TO INCREMENT CORE DATA

Thomas B. Lynch and Robert F. Wittwer¹

ABSTRACT.—Per tree estimates using the n trees nearest a point can be obtained by using a ratio of per unit area estimates from n -tree distance sampling. This ratio was used to estimate average age by d.b.h. classes for cottonwood trees (*Populus deltoides* Bartr. ex Marsh.) on the Cimarron National Grassland. Increment cores were sampled from the two cottonwoods closest to a plot center. Within each d.b.h. class, a ratio was obtained with the two-tree estimates of the sum of the sample tree ages in the numerator and the number of trees per acre in the denominator. This ratio estimated average age within the class.

Tree attributes that are time consuming or laborious to obtain, such as increment cores, have often been sampled by selection from a fixed number of trees nearest to a plot center or point located in the field. Per tree estimates such as average age or 10-year increment have then been computed by using simple averages from sample cores (or other attributes), often by d.b.h. classes. Clutter and others (1983) correctly noted that estimation using simple averages with these data is problematic because trees that occupy larger amounts of space are more likely to be selected by this procedure. Thus, trees associated with specified attributes are not sampled in proportion to their frequency in the population. Clutter and others (1983) recommend that increment cores be selected from all trees located within the boundaries of small fixed-sized sample plots. However, the problems associated with selection of increment cores or other attributes from the n sample trees nearest to a point can also be discussed within the framework of n -tree distance sampling.

***N*-TREE DISTANCE SAMPLING**

N -tree distance sampling is based on selection of the n trees closest to a sample point located in the forest population of interest. Plot size is circular based on a radius to the center of the most distant of the n trees closest to the point, so that all

n trees are in the plot (fig. 1). The estimate of trees per acre from n -tree sampling with m sample points is

$$T_A = \frac{1}{m} \left(\frac{n-1}{n} \right) \sum_{i=1}^m \frac{n}{A_i} \quad (1)$$

where

R_{ni} = distance to tree n on plot i in feet,

$A_i = \pi \cdot \frac{R_{ni}^2}{43,560}$ area of plot i in acres,

m = number of n - tree plot locations, and

T_A = estimated number of trees per acre.

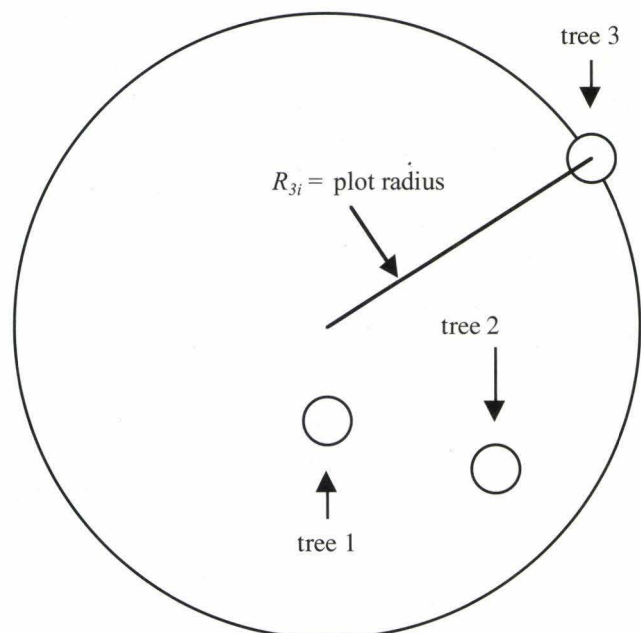


Figure 1.—Plot for n -tree sampling with $n = 3$.

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The estimator above would be similar to a fixed-radius plot estimator except for multiplication of the factor $(n-1)/n$. Moore (1954) derived this factor to correct for the bias that would otherwise occur when the spatial arrangement of trees is according to the Poisson distribution characteristic of a random pattern. Thompson (1956) derived the distribution of the distance to the n^{th} individual when individuals are randomly distributed on a plane. Eberhart (1967) showed that the use of the factor $(n-1)/n$ is correct for the negative binomial distribution sometimes characteristic of clumped spatial patterns as well as for the Poisson distribution. Per acre estimates of other tree attributes can be obtained by accumulating the attributes of trees on the n -tree sampling plot

$$Y_A = \frac{1}{m} \left(\frac{n-1}{n} \right) \sum_{i=1}^m \frac{\sum_{j=1}^n Y_{ij}}{A_i} \quad (2)$$

where

Y_{ij} = amount of characteristic Y on tree j at plot i , and

Y_A = estimated amount of characteristic Y per acre.

Lessard and others (1994) used these n -tree methods to estimate volume, basal area, and number of trees per acre in typical northern hardwoods, red pine plantations, and sprout-origin aspen-birch (typically clumped) forest types. They achieved results that compared well with those obtained by more traditional forest inventory methods including fixed-radius plot and point (angle-gauge) sampling.

N-TREE SAMPLING WITH PER TREE ESTIMATES

Estimates of per tree attributes can be obtained by using the ratio of the quantity of an attribute per acre to the number of trees per acre having that attribute. Estimators for the latter quantities can be obtained using the n -tree distance sampling estimators given above. The ratio estimate for per tree attributes from n -tree distance sampling is

$$\bar{Y}_{pt} = \frac{Y_A}{T'_A} = \frac{\frac{1}{m} \left(\frac{n-1}{n} \right) \sum_{i=1}^m \frac{\sum_{j=1}^n Y_{ij}}{A_i}}{\frac{1}{m} \left(\frac{n-1}{n} \right) \sum_{i=1}^m \frac{\sum_{j=1}^n I_{ij}}{A_i}} = \frac{\sum_{i=1}^m \frac{\sum_{j=1}^n Y_{ij}}{A_i}}{\sum_{i=1}^m \frac{\sum_{j=1}^n I_{ij}}{A_i}} \quad (3)$$

where

I_{ij} is 1 if tree j on plot i has attribute Y , otherwise 0,

T'_A is the estimated number of trees per acre having attribute Y , and

$\bar{Y}_{pt}$ is the estimate for the average amount of attribute Y per tree.

It is of interest to note that the ratio estimate $\bar{Y}_{pt}$ does not depend on the bias correction factor $(n-1)/n$ since it is eliminated by division of per acre estimates when the ratio is formed. This suggests $\bar{Y}_{pt}$ may be robust in application to forests that have spatial arrangements for which the bias correction factor $(n-1)/n$ may not be correct.

ESTIMATING AVERAGE TREE AGE ON THE CIMARRON NATIONAL GRASSLAND

The ratio estimate of equation 3 above was used to estimate the average age per tree in a recent inventory of the tree resources of the Cimarron National Grassland, located in southwestern Kansas. Eastern cottonwood is the predominant species making up the riparian forest along a 25-mile-long corridor surrounding the Cimarron River within the grassland. Nineteen sample transects crossing the riparian area surrounding the river from north to south were established at points randomly located from the western border of the grassland. The band of trees in the river corridor is surrounded by semi-arid grassland. Each transect covered the width of the tree band. Fixed-radius 0.1-acre (0.2 acre on the first two transects) sample plots were established at 6-chain (396 feet) intervals along each transect on which sample trees were selected to estimate the number of trees per acre and basal area per acre. Thus, the number of plots per transect varied according to the width of the riparian forest. This was an unequal-sized cluster sampling design (Sukhatme and others 1984) in which the transects consisted of clusters of plots. Two cottonwood trees (three on the first two transects) nearest each plot center were selected for increment core extraction to determine tree age. Cores were collected and aged in the laboratory where phloroglucinol staining was used to enhance separation between springwood and summerwood as recommended by Patterson (1959) for diffuse porous species. Cottonwood trees ranging from seedlings to trees 47 inches in d.b.h. were sampled. On average, 94 cottonwood trees per acre were greater than 4.5 feet tall, of which 34 per acre were greater than 3.5 inches in d.b.h.

Equation 3 was used to estimate average age per tree within 1-inch d.b.h. classes for cottonwood on the Cimarron National Grassland. Standard errors were estimated using methods appropriate for the ratio of sample means (Cochran 1977). For comparison, ages within d.b.h. classes were also calculated by a simple arithmetic average of increment cores within the selected class.

Table 1.—Estimates of average age for selected 1-inch d.b.h. classes on the Cimarron National Grassland from a ratio of *n*-tree sampling estimates and from unweighted arithmetic averages of increment cores

D.b.h. class midpoint (inches)	Ratio estimate of average age (yrs) (standard error)	Unweighted average age (yrs) (standard error)
3	12.0(0.1)	13.2(1.2)
16	60.4(4.3)	46.7(3.9)
31	79.0(3.4)	79.6(2.8)

Table 1 indicates that the two methods of average age estimation give results that are quite close in the 3-inch and 31-inch classes. However, estimates could be substantially different, as was the case in the 16-inch d.b.h. class where the greatest difference in age estimates was observed.

Inspection of the data in the 16-inch d.b.h. class indicated that one of the older cores was extracted from a tree located on an unusually small *n*-tree plot. Cottonwood tends to grow in clumps, so if the sample point falls in a clump of two or more trees, it is possible to obtain a rather small plot in two-tree sampling. Equation 3 is similar to a weighted average of increment core data where the weights are the inverse of the *n*-tree plot sizes. Thus, observations associated with small plot sizes have more weight than those associated with larger plot sizes. Therefore, in the 16-inch classes, the older core received more weight and caused the resulting average age estimate to be larger than the simple arithmetic average of the core data. Of course, this weighting is usually desirable and helps to overcome the objections of Clutter and others (1982) to the use of nearest-neighbor tree data for per tree estimation. There is a tendency for trees on smaller plots to grow in higher densities and therefore to have smaller probability of selection by nearest-neighbor methods. Weighting by inverse plot size helps to account for this when data are used in estimators such as equation 3.

SUMMARY AND DISCUSSION

Generally it should be desirable to use equation 3 to estimate per tree attributes when the *n* nearest trees are selected as sample trees. This method helps avoid the objections of Clutter and others (1983). In the context of *n*-tree sampling for per hectare attributes, Jonsson and others (1992) recommended sampling all trees within a small fixed-radius plot in cases where the *n*-tree plot radius was smaller than a given fixed amount (they used 3 m for 6-tree to 13-tree sampling). However, Jonsson and others (1992) did not discuss estimation of per tree attributes. A ratio of per acre estimates from *n*-tree sampling was used to estimate average ages by d.b.h. class on the Cimarron National Grassland. In most d.b.h. classes, these estimates were not greatly different from simple arithmetic averages of increment core data, but, there were fairly substantial differences in a few classes. The estimate of average age given by the ratio of per acre *n*-tree estimates should be preferable since it accounts for the variation in *n*-tree plot sizes and corresponding fluctuations of density within the tree population.

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STANDARD ERRORS IN FOREST AREA

Joseph McCollum¹

ABSTRACT.—I trace the development of standard error equations for forest area, beginning with the theory behind double sampling and the variance of a product. The discussion shifts to the particular problem of forest area—at which time the theory becomes relevant. There are subtle difficulties in figuring out which variance of a product equation should be used. The equations developed may be extended to other areas of forest inventory.

What follows is a development of standard error equations. Key topics include double sampling and the variance of a product. Applications to calculation of the variance of forest area follow.

Although the following equations seem very abstract at first glance, they are highly relevant to the development of standard error equations in computation of forest area.

Goodman (1960) pointed out that if $Z = XY$, then

$$\sigma_Z^2 = \mu_X^2 \sigma_Y^2 + \mu_Y^2 \sigma_X^2 + \sigma_X^2 \sigma_Y^2 \quad (1)$$

for X and Y independent, where

σ_A^2 denotes the variance for the subscripted variable A ,
 μ_A denotes the true mean for the subscripted variable A ,
 and
 A denotes X , Y , or Z , as appropriate.

Goodman (1962) showed that if the means and variances are not known, then an unbiased estimator is

$$s_Z^2 = \bar{X}^2 s_Y^2 + \bar{Y}^2 s_X^2 + \frac{n_X n_Y - n_X - n_Y}{n_X n_Y} \cdot s_X^2 s_Y^2 \quad (2)$$

for X and Y independent, where

$\bar{A}$ denotes the sample mean for variable A (also represented by m_A),
 s_A^2 denotes the sample variance for variable A ,
 n_A denotes the number of observations for variable A ,
 and
 A denotes X , Y , or Z , as appropriate.

If we let $X = \bar{X}$ and $Y = \bar{Y}$ then,

$$s_Z^2 = \bar{X}^2 s_Y^2 + \bar{Y}^2 s_X^2 + \frac{n_X n_Y - n_X - n_Y}{n_X n_Y} \cdot s_X^2 s_Y^2 \quad (3)$$

If $n_X = n_Y = n$, then

$$s_Z^2 = \bar{X}^2 s_Y^2 + \bar{Y}^2 s_X^2 + \frac{n-2}{n} \cdot s_X^2 s_Y^2 \quad (4)$$

Let us see how these equations work with real data. Suppose you have independent Bernoulli variables that take on the value 1 with probability 0.5 and zero otherwise. You have decided to take two samples of each variable. The experiment may give results in 16 possible ways, shown in table 1.

On the other hand, suppose that you were not interested in $Z = XY$, but rather in $W = \bar{X} \cdot \bar{Y}$.

If $W = \bar{X} \cdot \bar{Y}$, then $n_X = n_Y = 1$, and

$$s_W^2 = \bar{X}^2 s_Y^2 + \bar{Y}^2 s_X^2 - s_X^2 s_Y^2 \quad (5)$$

where

s_A^2 denotes the standard error of the mean for variable A (also represented by $s^2(m_A)$).

n_A denotes the number of observations used to form the sample of W (which is one observation), and

k_A denotes the number of observations used to form the sample of variable A .

The k_A does not appear in the equation directly. Again, the experiment may give results in 16 possible ways, shown in table 2.

In table 2, $k_X = 2$ and $k_Y = 2$. However, $k_W = n = 1$. At first, it seems strange that an experiment with one observation could have a variance at all. However, suppose we think of the 16 possible results of the experiment as 16 possible worlds. Equation (5) gives the variance of $W = \bar{X} \cdot \bar{Y}$ among those 16 possible worlds.

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Table 1.—Bernoulli variables demonstrating Goodman's 1962 equations

	X_1	X_2	Y_1	Y_2	Z_1	Z_2	$s^2(Z)$	$s^2(mz)$	Eq. (2)	Eq. (3)
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0	0
4	0	0	1	1	0	0	0	0	0	0
5	0	1	0	0	0	0	0	0	0	0
6	0	1	0	1	0	1	0.5	0.25	0.25	0.125
7	0	1	1	0	0	0	0	0	0.25	0.125
8	0	1	1	1	0	1	0.5	0.25	0.5	0.25
9	1	0	0	0	0	0	0	0	0	0
10	1	0	0	1	0	0	0	0	0.25	0.125
11	1	0	1	0	1	0	0.5	0.25	0.25	0.125
12	1	0	1	1	1	0	0.5	0.25	0.5	0.25
13	1	1	0	0	0	0	0	0	0	0
14	1	1	0	1	0	1	0.5	0.25	0.5	0.25
15	1	1	1	0	1	0	0.5	0.25	0.5	0.25
16	1	1	1	1	1	1	0	0	0	0
Mean	0.5	0.5	0.5	0.5	0.25	0.25	0.1875	0.09375	0.1875	0.09375

Table 2.—Bernoulli variables demonstrating Goodman's 1960 equations

	X_1	X_2	Y_1	Y_2	m_x	m_y	$s^2(m_x)$	$s^2(m_y)$	Eq. (5)	$Z=m_x m_y$
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	1	0	0.5	0	0.5	0	0
3	0	0	1	0	0	0.5	0	0.5	0	0
4	0	0	1	1	0	1	0	0	0	0
5	0	1	0	0	0.5	0	0.5	0	0	0
6	0	1	0	1	0.5	0.5	0.5	0.5	0.0625	0.25
7	0	1	1	0	0.5	0.5	0.5	0.5	0.0625	0.25
8	0	1	1	1	0.5	1	0.5	0	0.25	0.5
9	1	0	0	0	0.5	0	0.5	0	0	0
10	1	0	0	1	0.5	0.5	0.5	0.5	0.0625	0.25
11	1	0	1	0	0.5	0.5	0.5	0.5	0.0625	0.25
12	1	0	1	1	0.5	1	0.5	0	0.25	0.5
13	1	1	0	0	1	0	0	0	0	0
14	1	1	0	1	1	0.5	0	0.5	0.25	0.5
15	1	1	1	0	1	0.5	0	0.5	0.25	0.5
16	1	1	1	1	1	1	0	0	0	1
Mean	0.5	0.5	0.5	0.5	0.5	0.5	0.25	0.25	0.078125	0.25
Var	0.25	0.25	0.25	0.25	0.125	0.125				0.078125

In that same table, we see that the variance of $W = \bar{X} \cdot \bar{Y} = m_X \cdot m_Y$ is on average equal to Goodman's estimator of 1960. Goodman showed this result in 1960; he pointed out the irony of subtracting the third term for the estimator but adding it in the theoretical case. Also, in this table, I would like to point out that if instead of 0,1 variables there were -1,+1 variables, Goodman's estimator of 1960 would produce a negative estimate of the variance—an impossibility—in 4 out of 16 cases. Nonetheless, the estimator is still unbiased. This result may make Goodman's estimator unusable to some analysts. There are at least several alternatives; one is to set the estimate equal to zero if it is negative; however, the estimator would no longer be unbiased. Another possibility would be to take a sample size so large that the size of the third term would be insignificant. One last option would be to realize that the variable of interest has a high coefficient of variation.

At this point, the reader might wonder when Goodman's equations can be put to practical use. Two examples follow. The first example illustrates the use of Goodman's equation of 1962. It involves the combination of two data sets that have been partially matched; Goodman's equation of 1962 requires paired data. It involves the calculation of an observation times an observation. The larger data set is collected by photo-interpreters. The smaller data set is a subset of the larger one, which is collected by field crew. The assumption is that the photointerpreters' accuracy rate for the points that the field crew does not check is the same as their accuracy rate for the points that the field crew does check.

The second example is an illustration of Goodman's equation of 1960. It involves the calculation of the variance of an unknown proportion—it is an average times an average. The mean and variance of each component is known, and thus a variance of the product may be computed.

APPLICATION TO FOREST AREA

Goodman's equations may be used to derive the traditional standard error equations of forest area.

A forest inventory begins with a photointerpretation phase, known as phase 1. Aerial photographs are scored with dots, and the photointerpreters call each dot either "forest" or "nonforest." A phase 1 estimate is the proportion of dots believed to be forested. The photointerpreter is to consider

only the immediate neighborhood of the dot, not the entire area nearest a dot.

Among the dots on the aerial photographs are 1) regular plots, which field crews visit, measure the conditions and trees on the plots and 2) intensification plots, which field crews visit, call either "forest" or "nonforest," but make no other measurements.

The phase 2 estimate is the Bayesian expectation of forested land based on the photointerpreter calls and the field crew calls. This result typically has a much lower variance than the phase 1 estimate. Suppose there are n_{ij} plots called class i in phase 1 and class j in phase 2. If there are two classes, there would be $n_{\cdot 1} = n_{11} + n_{21}$ forested plots and $n_{\cdot 2} = n_{12} + n_{22}$ non-forested plots.

Let

$d = \sum_{i=1}^I d_i$ denotes the total number of dots,

$P_i = \frac{d_i}{d}$ denotes the phase 1 estimate for class i ,

$n_{\cdot j} = \sum_{i=1}^I n_{ij}$ denotes the total number of plots in class j ,

$p_{ij} = \frac{n_{ij}}{n_{\cdot j}}$ denotes the proportion of plots in class j of phase 2 that were in class i of phase 1.

$P_{ij} = P_i \cdot p_{ji}$ denotes the adjusted proportion of the landscape believed to be in class i of phase 1 and class j of phase 2, and

$P_{\cdot j} = \sum_{i=1}^I P_{ij}$ denotes the phase 2 estimate for class j ,

where

I is the number of classes.

There is then a tabulation such as the following:

d ₁	=	1200	d ₂	=	1300
P ₁	=	0.48	P ₂	=	0.52
n ₁₁	=	45	n ₁₂	=	3
n ₂₁	=	5	n ₂₂	=	57
n _{•1}	=	50	n _{•2}	=	60
p ₁₁	=	0.90	p ₁₂	=	0.05
p ₂₁	=	0.10	p ₂₂	=	0.95
P ₁₁	=	0.4320	P ₂₁	=	0.0480
P ₂₁	=	0.0260	P ₂₂	=	0.4940
P _{•1}	=	0.4580	P _{•2}	=	0.5420

In this case, at the end of phase 1, the proportion of area believed to be forested would be 48 percent. At the end of phase 2, the proportion is adjusted to 45.8 percent.

What is a confidence interval on this estimate?

If the user is interested in a confidence interval on the proportion of forested land of a randomly chosen acre of ground, then what is desired is $Var(\bar{P}_{•1})$. However, more commonly, what is desired is a confidence interval on the mean proportion across the landscape, or $Var(\bar{P}_{•1})$.

$$Var(\bar{P}_{•1}) = Var(\overline{p_{11}P_1}) + Var(\overline{p_{12}P_2}) + 2Cov(\overline{p_{11}P_1}, \overline{p_{12}P_2}) \quad (6)$$

The factors in each term are observations; therefore Goodman's equation of 1962, or equation (3) in this paper, should be used.

$$Var(\overline{p_{1k}P_k}) \approx P_k^2 \frac{p_{1k}(1-p_{1k})}{n_{•k}} + p_{1k}^2 \frac{P_k(1-P_k)}{d} = Q \quad (7)$$

Equation (7) says that the variance of a product of independent variables is approximately equal to the square of the mean of the first factor times the variance of the second factor plus the square of the mean of the second factor times the variance of the first factor. Kish (1965) offered this approximation.

$$Var(\overline{p_{1k}P_k}) = Q + \frac{n_{•k}d - n_{•k} - d}{n_{•k}^2 d^2} p_{1k}(1-p_{1k})P_kP_2 \quad (8)$$

Equation (8) is an implementation of equation (3).

$$Cov(\overline{p_{11}P_1}, \overline{p_{12}P_2}) = \frac{-p_{11}p_{12}P_1P_2}{d} \quad (9)$$

The factors p_{11} and p_{12} are independent of the others; P_1 and P_2 sum to 1.

By combining equations (5), (6) (first where $k = 1$ and then where $k = 2$), and (8),

$$Var(\bar{P}_{•1}) \approx P_1^2 \frac{p_{11}(1-p_{11})}{n_{•1}} + P_2^2 \frac{p_{12}(1-p_{12})}{n_{•2}} + \frac{P_1P_2}{d}(p_{11}-p_{21})^2 = V \quad (10)$$

According to Dr. James Rosson (USDA Forest Service, personal communication), DeLury developed this equation (circa 1950).

Two additional terms from equation (8) may be added for an exact answer, which is

$$Var(\bar{P}_{•1}) = V + \frac{n_{•1}d - n_{•1} - d}{n_{•1}^2 d^2} p_{11}(1-p_{11})P_1P_2 + \frac{n_{•2}d - n_{•2} - d}{n_{•2}^2 d^2} p_{12}(1-p_{12})P_1P_2 \quad (11)$$

In the example, the standard error of the mean is equal to 2.63 percent if both phase 1 and phase 2 are considered; it is nearly 4.75 percent if only the phase 2 plot coordinates are considered.

This method works for a sample. Card (1982) offered an alternate method for a full census (such as what might be involved in remote sensing). Remote sensing is the analysis of digital satellite images. Every point on the landscape cannot be photointerpreted; rather, a finite sample must be taken. However, a digital image may be analyzed wall-to-wall. The caveat is that it may be analyzed at the resolution of the data. There may be surface water, nonforested land, and forested land in one pixel; the satellite sensor will record an average of sorts for that pixel.

VARIANCE ESTIMATES OF A KNOWN PROPORTION

The amount of area in a particular State (A_t) is a legally defined amount. The proportion of forested land is not known; let it be represented by ϕ . If one desires to estimate the number of acres of forested land (A_{fr}), then

$$E(A_{fr}) = A_t \phi \quad (12)$$

The variance on this estimate is

$$\sigma^2(A_{ft}) = A_t^2 \cdot \frac{\varphi \cdot (1 - \varphi)}{n_t} \quad (13)$$

The standard deviation is

$$\sigma(A_{ft}) = A_t \sqrt{\frac{\varphi \cdot (1 - \varphi)}{n_t}} \quad (14)$$

To get the answer in terms of a proportion, divide both sides by A_t

$$\frac{\sigma(A_{ft})}{A_t} = CV(\varphi_t) = \sqrt{\frac{\varphi \cdot (1 - \varphi)}{n_t}} \quad (15)$$

One might call this quantity the coefficient of variation on the proportion of forest for the total.

Suppose one is interested in only a portion of a State (A_s).

Suppose $p = A_s/A_t$. If the State's land is relatively homogeneous, then

$$E(A_{fs}) = A_s \varphi \quad (16)$$

The variance on this estimate is

$$\sigma^2(A_{fs}) = A_s^2 \cdot \frac{\varphi \cdot (1 - \varphi)}{n_s} \quad (17)$$

The standard deviation is

$$\sigma(A_{fs}) = A_s \sqrt{\frac{\varphi \cdot (1 - \varphi)}{n_s}} \quad (18)$$

Divide both sides by A_s to get the coefficient of variation

$$\frac{\sigma(A_{fs})}{A_s} = CV(\varphi_s) = \sqrt{\frac{\varphi \cdot (1 - \varphi)}{n_s}} \quad (19)$$

If we divide equation (19) by equation (15), we get

$$\frac{CV(\varphi_s)}{CV(\varphi_t)} = \frac{\sigma(A_{fs})}{\sigma(A_{ft})} \cdot \frac{A_t}{A_s} = \sqrt{\frac{n_t}{n_s}} = \sqrt{\frac{1}{p}} \quad (20)$$

which is what FIA reports have published for many years.

VARIANCE ESTIMATES OF AN UNKNOWN PROPORTION

There are other aspects of forest inventory where the proportion under consideration is unknown. Although it is a variable no longer collected, wetland status was a subjective call. Photointerpreters did not attempt to delineate wetland

timberland from other timberland. Quality assurance crews did check a number of plots a second time, but cross-tabulation data were not kept. If such data had been kept, the double-sampling equations could be used.

The first temptation would be to use a single-sampling equation. Suppose that one-half of the land is believed to be forested in a particular county, with a standard error of 2 percent. Also suppose that 10 percent of the forested plots were judged to be wetland by the field crews. There are 100 plots in the county, and the average acreage expansion factor is 6,000.

Under a single-sampling model, $\varphi = 0.05$, the standard error of which is 0.021794; thus one can say with 67 percent confidence that between 16,923 and 43,076 acres are wetland timberland.

However, if acreage expansion factor in thousands of acres (X) and wetland status (Y) are independent, then equation (5) may be used. It is generally impossible to assign an exact number of acres to particular plots; instead averages are used. For instance, if there are 300,000 plus or minus 6,000 forested acres in the county, and there are 50 forested plots, then on average there are 6,000 acres per plot. From equation (20), the standard deviation on 6,000 acres and one plot is 848.5.

However, unless more information is known (such as the total number of acres in particular ownership classes), then every plot is assigned an acreage expansion factor of 6,000—some don't get 5,900 while others get 6,100.

In this case, $\bar{X} = 300$, $s_X^2 = 36$, $\bar{Y} = 0.1$, $s_Y^2 = 0.09$, and $s_{\bar{W}}^2 = 300^2 \cdot 0.09 + 0.1^2 \cdot 36 - 0.09 \cdot 36$, or 8,097. There are 50 observations, so the standard error of the mean is 12,725. One can then say with 67 percent confidence that in this county, there are between 17,275 and 42,725 acres of forested wetland—in this case there is only a small improvement over the single-sampling equation.

CONCLUSIONS

Although the long-term plan is to do phase 1 estimates by remote sensing, it was a useful exercise to document equations that could be used to estimate standard errors in forest area. They may be adapted to other topics in forest inventory, such as extent to which quality control should be done and the development of standard error equations for the number of

trees, volume, biomass, as well as growth, removals, and mortality.

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A FIRST LOOK AT MEASUREMENT ERROR ON FIA PLOTS USING BLIND PLOTS IN THE PACIFIC NORTHWEST

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ABSTRACT.—Measurement error in the Forest Inventory and Analysis work of the Pacific Northwest Station was estimated with a recently implemented blind plot measurement protocol. A small subset of plots was revisited by a crew having limited knowledge of the first crew's measurements. This preliminary analysis of the first 18 months' blind plot data indicates that ranges of variation can be quite large. When blind plot results were summarized to facilitate comparisons with established tolerance standards, we found that diameters at breast height for trees > 20 inches d.b.h., heights for trees < 60 feet tall, and counts of down wood pieces did not meet standards in over 10 percent of cases. However, azimuths for condition class boundaries, diameters for trees ≤ 20 inches d.b.h., heights for trees ≥ 60 feet tall, and understory vegetation cover estimates by life form were within tolerance limits at least 90 percent of the time.

Forest Inventory and Analysis (FIA) timber resource bulletins are typically accompanied by estimates of standard errors based on the underlying sampling design. Efforts to quantify and account for error due to measurement variation are underway. FIA programs nationally employ systems of Quality Assurance/Quality Control (QA/QC or simply QA) under which trained personnel revisit plots and determine whether crew data are within measurement tolerances (commonly referred to as Management Quality Objectives, or MQOs). The blind plots used in this study differ from standard QC checks, typically performed for feedback, training, or certification of accomplishment of contract standards, in that regular production field crews were employed at both visits, rather than a QA crew. This captures variation between two relatively independent measurements collected in a normal manner at the same field location.

METHODS

Blind Plot Field Protocol

The FIA program at the Pacific Northwest Research Station instituted blind plots during the 2000 field season. However, protocols have evolved somewhat since then to achieve more unbiased and complete estimates of measurement error (table 1). Because PNW is transitioning from several regionally and temporally inconsistent inventory designs to a new, nationally adopted design, this analysis incorporates data collected on four plot layouts. These designs all consist of a base point from which other points were established in various directions. Each point marks the center of a circular subplot where data on trees larger than 5 inches diameter at breast height (d.b.h.) were collected. Western (3 points in 2000, 10 blind plots) and eastern Washington (4 points in 2001, 15 blind plots) use 55.8- and 32.8-foot maximum radii for variable-radius tree sampling, with understory vegetation collected on 6.8- and 16.4-foot subplots, respectively. Plots in the annual inventories in Oregon (2000, 10 blind plots; 2001, 3 blind plots) and California (2001, 8 blind plots) use the nationally adopted design of 24-foot fixed-radius points for tree sampling and understory vegetation (although Oregon 2000 used a 6.8-foot understory vegetation plot). Annular plots designed to more reliably determine the presence of large trees (the definition of large tree varies depending on the inventory) extend 58.9 feet from subplot center (Forest Inventory and Analysis program,

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Table 1.—Changes in blind plot protocols over the first 2 years of their implementation at PNW FIA

	2000	2001
Blind plots chosen by	field crew supervisors, based on access and ease of plot.	field crew supervisors, based on access to plot, and whether there is a condition class change or not.
Second crew receives	plot packet with all previous crews' information, including the information from the first visit of this year.	all old information from the plot, plus directions to the new plot from the first visit this year. No mapping information or data should be seen.
Second crew measures	d.b.h.s either at the old nail or where the crew felt was appropriate. coarse down wood transect placed either where first crew's was or where the second crew felt it was appropriate.	d.b.h.s at nail on subplots 1 & 2, where the crew felt was correct on subplots 3 & 4. coarse and fine down wood transects along bearing the second crew felt was correct.
Second crew estimates	understory vegetation. Site tree data not taken. New plotcard not written up.	understory vegetation. Site tree data collected. New plotcard written up, mapping performed.

2000a, 2000b, 2001a, 2001b). The following data were collected at all visited points.

Condition class: condition classes are defined by differences in status of one of six mapping variables (reserved status, forest type, owner group, stand size, regeneration status, and tree density). Boundaries between condition classes are recorded for all sizes of subplots as azimuths and distances to subplot edges from subplot center.

Tree measurements: 1) d.b.h.: stem diameter at 4.5 feet above the ground on the uphill side of the tree. Recorded in tenths of inches using a metal d.b.h. tape; 2) height: length of main bole from ground to tip of leader, recorded to the nearest foot using a laser or clinometer.

Understory vegetation: cover of shrubs, forbs, and grasses is visually estimated as a percent of area of a circular microplot/subplot—defined by a radius of 6.8, 16.4, or 24 feet, depending on the inventory. Total cover of all understory life forms (ignoring overlap) is also recorded.

Down wood: by annual inventory 2001 definitions, down wood is dead woody material on the forest floor greater than 0.01 inches in diameter. Fine down wood 0.01 to 0.9 inches in diameter is measured on one 10-foot transect per point, pieces 1.0 to 2.9 inches in diameter are recorded on a 20-foot transect, and coarse pieces ≥ 3 inches in diameter and ≥ 3 feet long are tallied on two 58.9-foot transects per point. All decay classes are included. Snags are considered coarse dead wood if they lean at an angle greater than 45 degrees from the vertical. Tally rules for 2000 inventories included only pieces > 5 inches across and 3.3 feet long, not supported by their root system, on three 55.8-foot transects per point. Decay classes 1 to 4 were recorded. Fine down wood was not assessed in 2000 inventories.

Analysis Protocol

Condition class: distance and azimuth data collected as part of plot mapping were used to determine the proportion of area of each subplot in each condition class. Estimates by the two field crews for each subplot were paired and difference in condition areas calculated.

Tree measurements: for tree analyses, trees over 5 inches d.b.h. were paired by tag number so differences between d.b.h. and height measurements could be obtained. In the interest of time, all trees not readily matched (e.g., due to labeling errors or use of generic '999' tree numbers) were excluded. Because some blind crews measured diameter at what they deemed to be breast height, while others measured diameter at the existing d.b.h. nail, it was not possible to determine which method was used for each tree, and no distinction was made in the analysis.

Understory vegetation: differences between estimates of understory vegetation cover were analyzed at the subplot level after excluding all subplots where both crews recorded 0 percent cover. Although these records are legitimate, we considered their inclusion likely to overstate the degree of agreement between crews. Because a number of periodic and annual inventory protocols were implemented over the last 2 years, understory vegetation data were collected on three different sizes of plots. In most cases this was assumed not to greatly affect the magnitude of differences between crew estimates, although some exceptions are noted below.

Down wood: for this analysis we assumed changing protocols would not affect the amount of measurement variation, so a unified database was constructed. To reduce potential design effects, differences were calculated in terms of number of pieces per 100 feet of transect. Plots where neither crew recorded woody debris were dropped, following logic analogous to the case for understory vegetation. Fine down wood, which was collected only in 2001, was also expressed as pieces per 100 feet of transect.

Several related questions of interest were briefly explored. To determine whether measurement variation increased with magnitude of the characteristic being measured, measurements of d.b.h., height, and understory vegetation cover were divided into classes and compared. We also explored whether height differences varied with measurement method. Three combinations are possible: both crews measured with laser or clinometer, both crews estimated, or one measured and the other estimated. Additional questions of interest for understory vegetation were whether magnitude of difference between estimates increased with plot size and whether measurements taken from the initial visit were consistently lower or higher than those from the blind visit. Tests for significant differences between categories used non-parametric statistical methods due to skewed distributions and numerous outlying

observations. All results reported as significant had one-sided p-values less than 0.05 by the Wilcoxon rank-sum test, unless otherwise noted.

RESULTS

Although every attribute had a few cases of extreme differences between crews, on average most differences were quite small (table 2). Close to half of the d.b.h. measurements and coarse down wood counts had no differences, and roughly a quarter of the understory vegetation measurements were identical between crews. Condition boundary azimuths, height measurements, and fine down wood counts showed less agreement, but median differences were not extreme, except possibly in the case of fine down wood.

Using the average of the two crews' measurements as the true value (e.g., of d.b.h. for each tree), MQOs were met at least 90 percent of the time for condition boundary azimuths, diameters on trees under 20 inches d.b.h., heights on trees 60 feet or taller, and cover for all understory vegetation cover categories (table 3). However, counts of small and large fine down wood were more often outside of tolerance limits than within them. If one crew's measurement was selected as the "true" value, then the only category where MQOs were met at least 90 percent of the time is percent cover of grass. MQOs for diameters on trees greater than 40 inches d.b.h., for heights of trees less than 60 feet tall, and for counts of all down wood were then not met in more than 50 percent of cases.

Did d.b.h. measurement error increase with tree diameter?

Evidence is convincing that it did (fig. 1). Median differences in tenths of inches for trees 5 to 20, 20.1 to 40, and 40.1 to 60 inches d.b.h. were 1, 1, and 4, respectively. All differences were significant (significant differences between medians of one-tenth inch occur because the test used is not based directly on the measured values, but on the ranks of values). However, if difference is expressed as percent of d.b.h. (estimated as the average of the two diameters at breast height), there is no evidence that trees in the smallest two classes had different median measurement errors, but median measurement error for trees 40.1 to 60 inches d.b.h. was significantly greater than for either lower class.

Did height measurement error increase with height? The answer depends on the measurement used. Dividing the tree data set into four height classes of 0 to 40 ($n = 185$), 40.1 to 80

Table 2.—Summary of values and differences obtained from 39 blind plots sampled in Washington, Oregon, and California during the 2000 and 2001 field seasons

Measurement	Number in sample	Range of measurements ^a	Range of differences	Median of differences	Mean	Percent of differences that are 0
Condition Class Boundaries (degrees)						
azimuths	64 azimuths	N/A	0 - 102	5	10	11
Trees						
d.b.h. (in.)	778 trees	5 - 54.2	0 - 20.1	0.1	0.2	45
height (ft)	778 trees	101 - 96	0 - 96	3	5	13
Understory Vegetation Cover (as percent area of understory vegetation plot)						
total	149 subplots ^b	1 - 99	0 - 75	6	12	20
shrub	135 subplots	1 - 99	0 - 50	5	8	24
forb	121 subplots	1 - 88	0 - 45	4	7	24
grass	108 subplots	1 - 68	0 - 50	2	6	27
Number of Pieces of Down Wood (by plot)						
coarse ^c	28 plots	1 - 7	0 - 3	1	1	43
fine ^d	11 plots					
	small (0.01-0.25 in.)	9 - 1,071	8 - 1,108	50	157	0
	medium (0.25-0.9 in.)	8 - 94	0 - 70	10	21	9
	large (1.0-2.9 in.)	4 - 39	1 - 31	5	9	0

^a Values averaged between crews.

^b Number of subplots varies because only those subplots where both crews recorded vegetation for a category were included.

^c Expressed as pieces per 100 feet of transect to reduce impact of design-based differences (see methods section for more detail).

^d Expressed as pieces per 100 feet for easier comparison to coarse down wood.

(n = 324), 80.1 to 120 (n = 210), and 120+ (n = 59) feet, median height differences increased with height—from 2 to 2 to 4 to 7 feet, respectively. If difference is expressed as percent of tree height (estimated as the average of the two heights), then trees under 40 and over 120 feet tall had the largest differences (median about 6 percent), while trees between 41 and 120 feet tall had between 4 and 5 percent median difference. The magnitudes of the differences vary depending on how the trees are classified into categories, but several different classifications produced identical patterns.

Were height measurement differences greater where tree heights were estimated? Not too surprisingly, yes. Median difference in measurement height (feet) increased from 2 where both crews measured, to 5 where only one measured, to 6 where both crews estimated (fig. 2). Differences between both measured vs. one measured and both measured vs. both estimated were significant.

Did differences between life form level understory vegetation cover estimates increase with the amount of cover in the life form? Figure 3 suggests, and rank-sum tests confirm, that variation between crews was generally highest when percent cover of a life form fell between 40 and 60 percent and the vegetation decreased as cover moved towards 0 or 100.

Did understory vegetation cover estimate differences increase with vegetation plot size? These data give no evidence of plot-size-influenced differences for total cover or cover of shrub species. Median differences for forb cover estimated on 6.8-foot radius plots were greater than for forb cover on both 16.4- and 24- foot radius plots. However, grass cover estimation seems more variable on 16.4-foot radius plots than on other plot sizes (fig. 4).

Table 3.—MQOs for the year 2001 shown with the percent of measurements not meeting these standards

Measurement	MQO	Percent not meeting MQO	
Condition Class			
boundaries	+/- 10 degrees at plot boundary	10 ^a	(31) ^b
area	none given	26	(39) ^c
Trees (by tree)			
d.b.h. ^d	+/- 0.1 in. for 5 to 20 in. d.b.h.	7	(23)
	+/- 0.2 in. for 20.1 to 40 in. d.b.h.	13	(26)
	+/- 0.3 in. for 40.1 to 60 in. d.b.h.	45	(55)
height	+/- 5% of true for <60 feet tall	28	(51)
	+/- 10% of true for ≥60 feet tall	4	(15)
Understory Vegetation (by subplot)			
cover percent	total cover +/-20 percent	7 ^e	(19)
	life form cover +/- 1 class ^f		
	shrubs	~3	(13)
	forbs	~3	(15)
	grasses	~1	(6)
Number of Pieces of Down Wood (by plot)			
coarse down wood	+/- 2 pieces or +/- 5 percent of pieces	46	(64)
fine down wood			
small (0.01-.24 in.)	+/- 20 percent for 0 to 50 pieces	55	(55)
	+/- 25 percent for 51 to 100 pieces		
	+/- 50 percent for 100+ pieces		
medium (0.25-0.9 in.)	+/- 20 percent of pieces	45	(55)
large (1.0-2.9 in.)	+/- 20 percent of pieces	55	(82)

^a Includes all condition class boundaries, regardless of size, on the same plot.

^b Amounts in parentheses are the percent of measurements that would not meet MQOs if one crew's answer was deemed the "true" value. In cases where MQOs changed at set levels, average values between crews were used to determine which tolerance standard applied, but the full difference was used to gauge error.

^c Of those 23 subplots where there was a condition class break involving condition class 1, 10 had a difference in the area assigned to condition class 1 that was ≥ 20 percent of the area of the subplot, using full differences.

^d Different from the numbers reported in the poster because several trees were initially included in error.

^e Vegetation cover percent and condition class data were reported as full differences between crew estimates for the poster. This was done because asymmetry of the tolerance classes (see next note) was thought to pose a problem. However, further analysis showed that it makes little difference for the data used here.

^f Vegetation cover tolerance classes are 1-5, 6-10, 11-20, 21-40, 41-60, 61-80, 81-100 percent. Crews actually collect cover data to the nearest 5 (sometimes 1) percent.

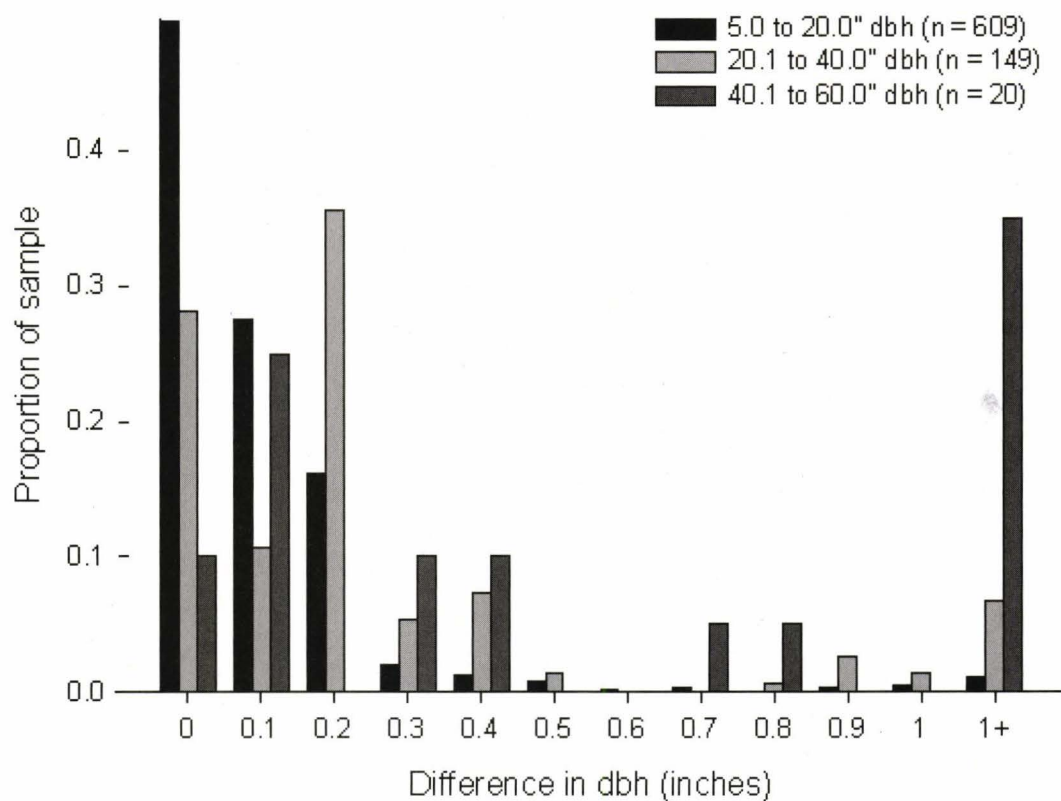


Figure 1.—Distribution of d.b.h. differences between crews, by d.b.h. class. Difference categories (in inches) are 0, from >0 to exactly 0.1, from >0.1 to exactly 0.2, and so on. The 1+ category represents differences ranging from >1.0 up to 20.1 inches.

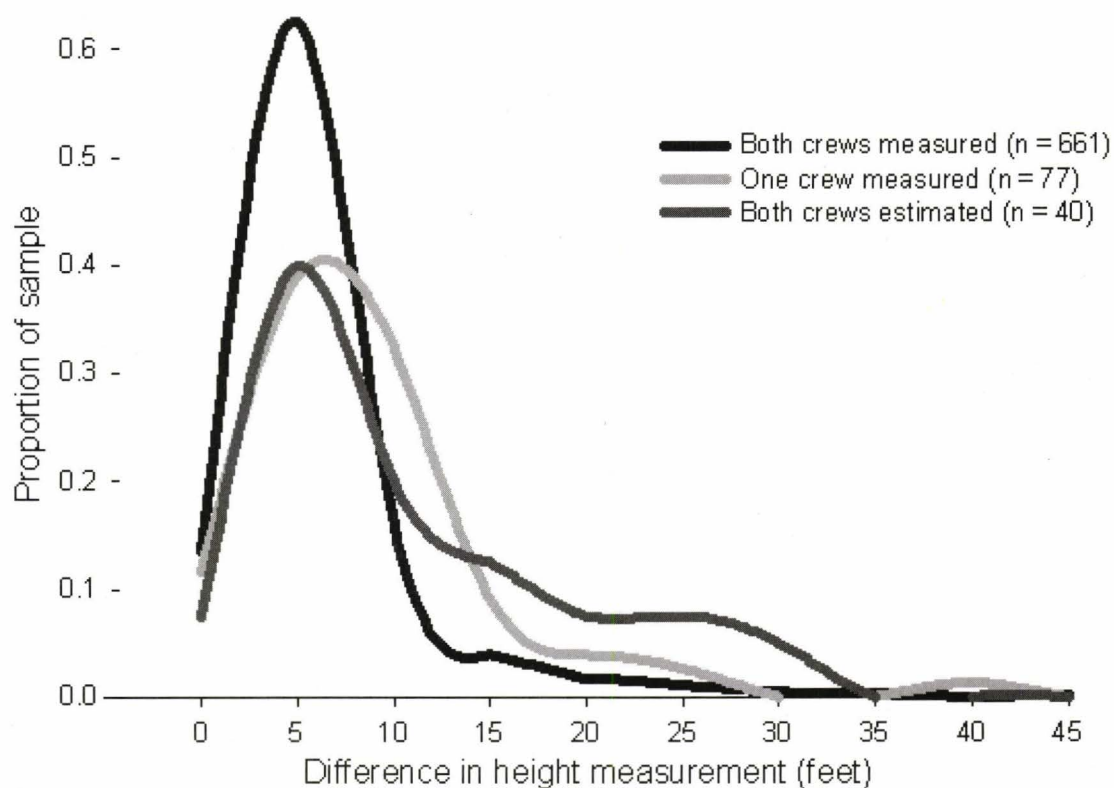


Figure 2.—Distribution of height differences between crews, separated by measurement technique.

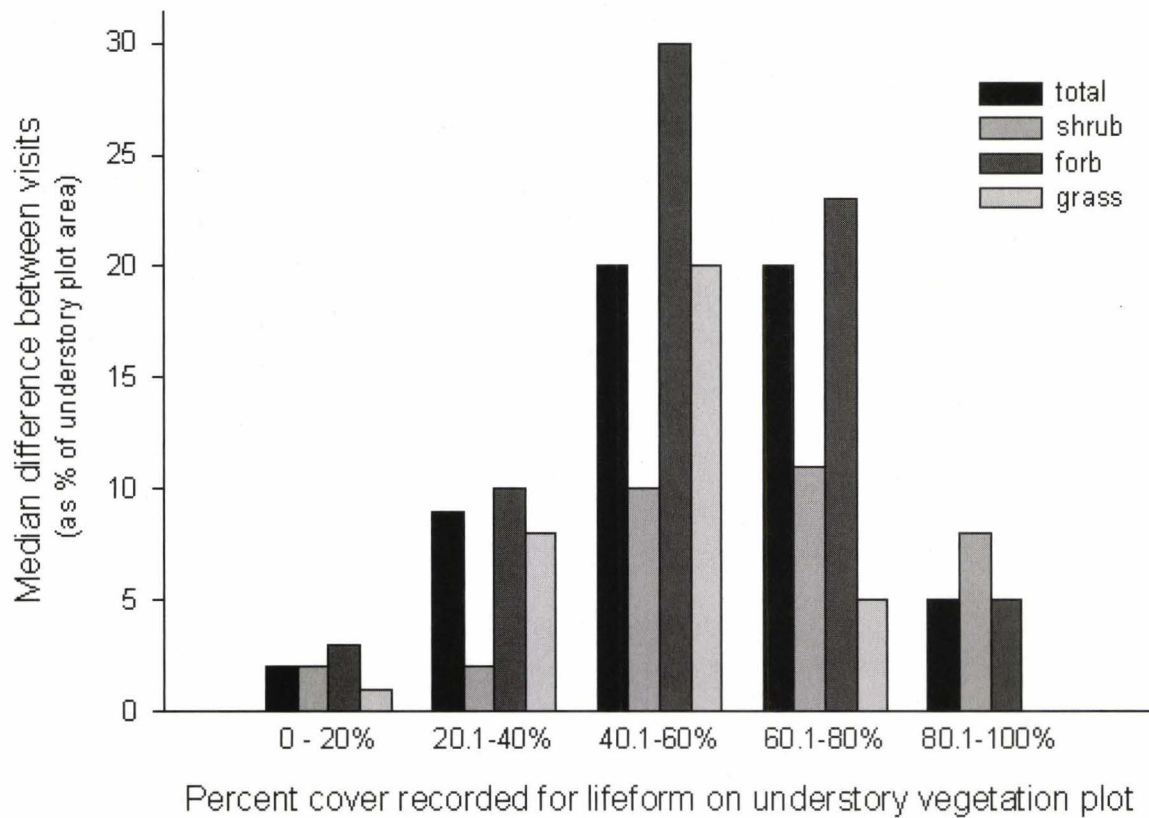


Figure 3.—Median differences between crew cover estimates for total vegetation and for life form.

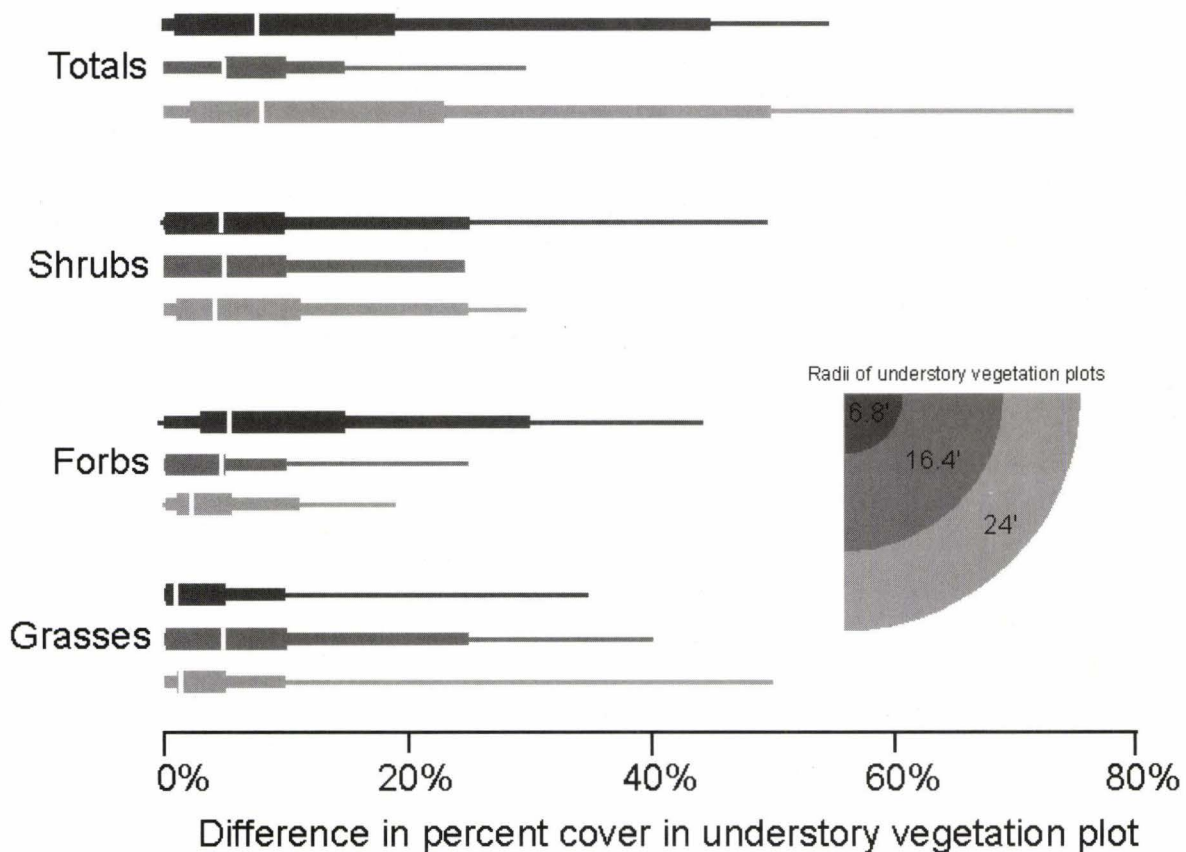


Figure 4.—Box plots of differences in understory vegetation cover estimates, by understory vegetation plot size. Thickest bar indicates inter-quartile range (the middle 50 percent of the differences), next-thickest shows extent of observations within 1.5 inter-quartile ranges from the box, and thinnest extends to cover all outliers. White line is the median difference.

Did one visit consistently produce higher understory cover estimates than the other? It appears that the first crews produced significantly higher estimates of cover for total understory vegetation, shrubs, and forbs; the second crews seem to have produced higher estimates of cover for grass (from Wilcoxon signed-rank tests). Exploratory analysis to determine if this could be related to number of days between visits or the season of the visits produced no significant results.

DISCUSSION

Computing differences between crew measurements is simple; comparing these differences to established MQOs is less so. Often tolerances are expressed as percentages of true values. When crew measurements are not identical, how can we identify or calculate the “true” value? Sometimes, permitted variation changes abruptly at some threshold. If the two crews’ measurements fall on opposite sides of that threshold, how can the correct tolerance be selected? There are few alternatives to defining the average of all paired measurements as our best estimate of the “true” value. Unfortunately, this is a maximally optimistic approach to error reporting because it minimizes differences between crew estimates and “truth.” It is thus likely that the number of plots/subplots/trees not meeting tolerances has been underestimated. Note that we have no basis for assuming that a QA crew’s measurements would fall directly between two production crews’ values. Analysis of several years’ stored data from QA plots may not help resolve this issue, since cold checks (where the QA crew inspects the plot without the original crew) have not been performed on blind plots, and cold check data were not always preserved as distinct data sets. Quality Assurance data by itself cannot be used to estimate measurement error since such checks were carried out by QA staff with the crew’s data in hand with little consistent protocol (i.e., not all attributes were checked and inspection was, in some instances, cursory). This likely produced greater agreement with production field crew results.

The nature of blind plots, in that regular crews conduct the second visit, is problematic as a basis for systematically assessing MQO achievement. While these data will likely prove useful in establishing how much measurement error can be expected for different plot attributes, which could, in turn, inform future revision and tuning of MQOs, MQO achievement would be better measured by stringent cold

checks. This would require the adoption of standard procedures and the training of all QA crews in measurement techniques that would produce measurements for every attribute that are as accurate and precise as possible.

Ranges of variation for most measurements were quite large. Many of the most extreme differences are almost certainly due to data entry error, yet they were not excluded from this analysis because it is unlikely that they would be detected during the data loading process.

As expected, condition class area assessment poses a problem for crews (Wilson and others 1999). Boundaries along roads are mapped with fair agreement, but the answer to the question, “when is a road its own condition class?” is not clearcut. Similarly, demarcations between vegetated condition classes are rarely obvious. Condition class area variability is further complicated by hazardous or inaccessible conditions not acknowledged by every crew. The number of subplots with condition class boundaries in this sample was small (24 out of 152 where at least one crew mapped a boundary). Better comparisons of variation between different types of condition changes can be made as additional blind plots are added to the database. Analysis of variation in mapping is further complicated when crews recognize different numbers of conditions on a subplot.

We expected d.b.h. measurement variability to increase with diameter, but not to the extent observed here (fig. 1). Of the 20 trees in the 40.1- to 60.0-inch class, the 7 with the largest differences were from a single plot. Inspection of d.b.h. measurement type codes revealed that they were almost all trees where non-standard measurement techniques (estimation or the half-diameter method) were used by at least one crew. As our sample of large tree blind measures increases, we will be better able to determine how common differences of this magnitude are.

Tree height error also varied unexpectedly. One might assume, and the more relaxed MQO on trees over 60 feet indicates, that the taller the tree, the more difficult it would be to measure accurately. This relaxed tolerance for tall trees accounts in part for more tall-tree heights being within the MQOs. Measurement difference in feet appeared to increase non-linearly with tree height. Therefore, when differences are expressed as percentages of (averaged) tree height (as specified in the MQOs), trees of medium height (between 50 and 150 feet tall) had smaller differences than those under or above that range. This does not explain why 28 percent of trees less than 60 feet tall did not meet their MQO, however. Perhaps crews simply

take more care with tall trees. More short trees may be growing in dense plantations where cruisers cannot get too far away lest they lose sight of the top or bole, or are hindered by vegetation and slash, and so end up taking measurements too close to trees, or where laser range finders used to measure height may more frequently sense the wrong tree. It may be that measurement instruments are used in a way where they will always produce a ± 2 foot difference, which is a negligible percent of a tall tree, but a larger portion of a shorter one. Measurement error is greatest for tree heights that were estimated (fig. 2), but both height classes have almost the same percent of trees that were estimated.

Previous studies (Sykes and others 1983) indicate that understory vegetation cover estimate differences are greatest in the middle ranges of cover, as was the case in this study for all understory life forms (fig. 3). We also expected to see an increase in estimate variability with increased plot size, but as Sykes and others observed (1983), this was not borne out by analysis (fig. 4). That may not rule out some effect of plot size; it could be masked by other factors influencing cover estimation, such as amount and height of vegetation present, slope, or season. Then again, it may be that size of the vegetation plot is not as important a factor as size of the crew. It was pointed out that the inventory using 16.4-foot

radius plots had a small number of people assigned to it, who may have worked in closer proximity, traded crew partners more frequently, and so may have kept inter-crew estimation variability low. Differences hypothesized due to different plot sizes may be so small compared to individual estimators' ranges of variation that they are impossible to detect through blind plots.

For this sample of plots, the first crew consistently recorded higher percentages of forbs, totals, and possibly shrubs. Where visits were only a few days apart, an obvious explanation for the discrepancy is trampling. For plots with more time between visits, seasonal effects could come into play. This might not always act to decrease the second crew's estimate, however. Some visits were separated by more than 80 days. Depending on time of the first visit and phenology of the species present, seasonal influences could increase, decrease, or have no effect upon the life form cover analyzed here.

Figure 5 demonstrates that the larger pieces of down wood had smaller count differences, although magnitude of errors was too great to see that trend reflected in the MQOs (table 3). Tolerance standards for small fines become increasingly lenient with abundance (table 3), yet the sometimes large inconsistencies (up to several hundred pieces difference per 10

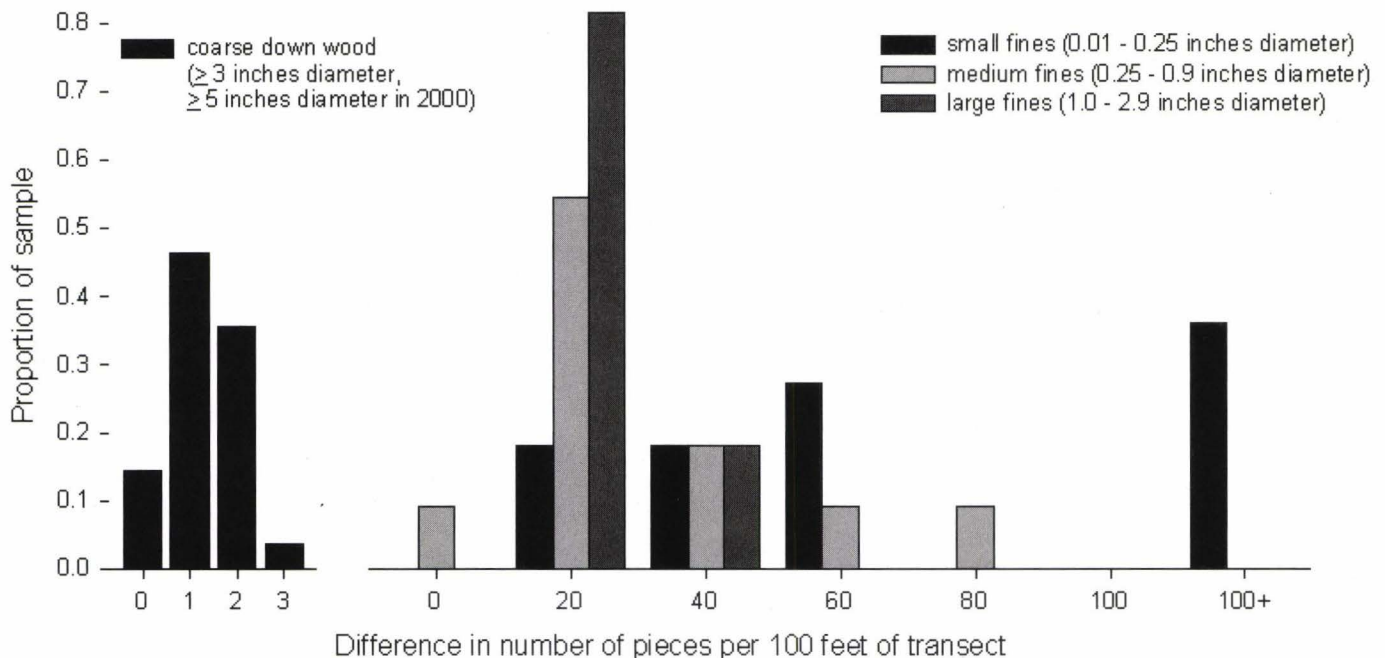


Figure 5.—Differences in counts of coarse down wood (left) and the three categories of fines (right) converted to number of pieces per 100 feet of transect for easier comparison.

feet for small fines) rendered even generous tolerances unattainable. This was the first year fines data were collected, so there may have been confusion with and inconsistent application of protocols. However, fine pieces are often numerous, hard to see, and easily moved, and therefore are difficult to count accurately. Note that for all fines data used here, blind plot protocol called for the transect to be placed where the second crew considered correct, so in some instances the same area might not be sampled. Obviously it is much easier to count larger pieces, yet even counts of coarse down wood are not entirely repeatable (again, transects may have followed slightly different azimuths).

This initial analysis represents a first step toward quantifying measurement error of various variables collected by PNW FIA crews. As more blind plots are completed, these estimates will be refined (15 plots per season are expected to be completed in each State—Oregon, Washington, and California). With more plots we should also be able to expand analyses in several directions. One such effort involves determining what effect measurement error might have on the reported standard error estimates. Examination of the effect on totals reporting should give some indication of whether these measurement variations are acceptable. From the preliminary results presented here, it is apparent that some measurements are quite inconsistent between crews. Large diameters at breast height, heights under 60 feet, and all down wood measurements are especially variable. There are three basic solutions to this: retraining crews with particular emphasis on attributes with high variability, revising measurement tolerances to make them more realistic, and redesigning measurement protocols.

Another question of interest is whether there are biases in field crew measurements. Of course, this requires knowledge of true values of measured attributes, a challenging bit of knowledge to obtain, so we may never reach a definitive answer.

Are the blind plots representative of the plot population as a whole? Perhaps that will not matter, since determination of measurement variation is the goal; crews could inventory areas that aren't plots at all and still produce estimates of measurement error. However, because we intend to extrapolate the results to all plots, if the sample used here was non-representative in some way that affected measurements, it could lead to inaccuracies in our predictions of measurement error. Future analyses will determine whether these plots reflect the plot population in terms of slope, distance from roads, density of understory vegetation, number of trees, range of tree ages and sizes, number of condition classes, proportion of private to public owners, and so on.

Since blind plots provide a repeat of all measures, in the future we will be able to extend this study to compare ranges of variation for every variable collected. This includes tree age, growth, damage, and crown measurements; site index; understory vegetation species counts and identification; ground cover transects; and fuel loading. This information, combined with calculations of sampling error, will be critical in assisting current and potential clients evaluate the fitness of FIA data for their intended uses.

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ANNUAL FOREST INVENTORY ESTIMATES BASED ON THE MOVING AVERAGE

Francis A. Roesch, James R. Steinman, and Michael T. Thompson¹

ABSTRACT.—Three interpretations of the simple moving average estimator, as applied to the USDA Forest Service's annual forest inventory design, are presented. A corresponding approach to composite estimation over arbitrarily defined land areas and time intervals is given for each interpretation, under the assumption that the investigator is armed with only the spatial/temporal matrix of moving average estimates. The advantages and practical limitations of each interpretation are discussed.

After a long history of conducting periodic inventories on a State-by-State basis, the USDA Forest Service's Forest Inventory and Analysis (FIA) program has initiated an annual forest inventory sampling design in which all forest land is sampled each year. The FIA units at the six Forest Service Research Stations are at various stages of implementing this common sampling design. The program at the Southern Research Station (SRS) has been known as the Southern Annual Forest Inventory System (SAFIS), e.g., see Roesch and Reams (1999). SAFIS was introduced to improve estimation of both the current resource inventory and changes in the resource. Within FIA, it is assumed that users will desire the ability to form estimates over arbitrary land areas and time intervals. It is also assumed that, because data are collected every year, users will expect to be able to obtain new information on an annual basis. However, the primary charge to FIA is to report on the state of the forest resource every 5 years using the data collected over the past 5 years. The design and intensity of the sample are intended to provide the ability to form estimates using 5 years' worth of data with the same degree of confidence as that available from the previous periodic surveys. FIA recognizes that a complete set of data will be available annually after the first 5 years of data have been collected but does not expect to have the resources necessary to publish complete reports annually. One proposal has been to make intermediate estimates based

on the moving average estimator available to a wide audience over the Internet. This would probably lead to questions as to how the moving average estimator should be interpreted, and how it should be used to form annual estimates and estimates of change over various time intervals. Below we present three simple interpretations of the moving average estimator along with their corresponding methods of making estimates over arbitrarily defined land areas. We also briefly mention some drawbacks to these approaches.

The plot arrangement for the annual FIA sample design resulted from an intensification of the National Forest Health Monitoring (FHM) grid, which has been described as a component of a global environmental monitoring sample design, e.g., Overton and others (1990) and White and others (1992). The sample plots are located in a systematic triangular grid with five interpenetrating panels. One panel per year is measured for 5 consecutive years. Every 5 years the panel measurement sequence reinitiates. If panel 1 was measured in 1998, it will also be measured in 2003, 2008, and so on. Panel 2 would then be measured in 1999, 2004, 2009, and so on. Figure 1 depicts the data availability from the panels for the first 10 years of measurement.

In the sequel, we assume that the user is interested in a specific classification of a particular area and time interval. Specifically, the classification must uniquely partition the area into mutually exclusive, all-inclusive classes. With respect to the sample, this requires the user to define the classification in such a way that a variable or a set of variables available in the data can be used to partition the sample into classes at discrete points in time. We show how the user could form estimates for each class within the defined area and time interval.

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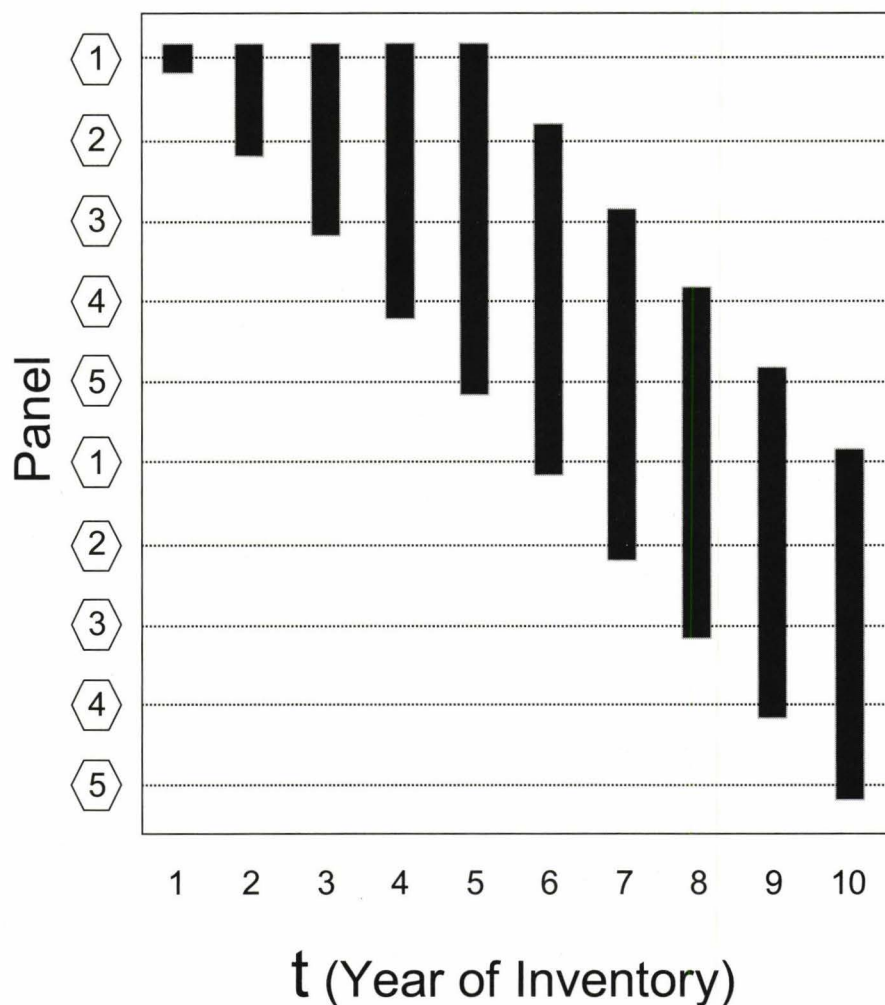


Figure 1.—Panel data availability from the five-panel annual FIA design. The panel enumeration represents successive years of measurement.

For example, one of the measured variables for each plot is the proportion of plot area in each forest condition class. Forest condition classes are at least an acre in size and identified by land use, forest type, stand origin, stand size, stand density, and ownership class (Anonymous 1998). The user might be interested in forming estimates for each forest condition class within a particular area and time period. Explicitly, the user has no interest in any area that is not defined as forest. Whatever classification is chosen, we recognize that it could be one that continuously changes through time, such as the above example that puts all nonforested areas into one class but separates forested areas into unique condition classes.

For practical purposes we need to fix the classification over discrete time intervals. In this paper, we will assume that the minimum usable interval is 1 year. This might be perceived as somewhat of a break with tradition since FIA has historically treated the classification as fixed over the entire measurement interval, which often consisted of several years.

Since it takes 5 years to measure all of the plots in the sample, the measurement interval is 5 years, but a new measurement interval is defined every year after the fifth year. These observations present opportunity in the guise of a dilemma. The dilemma exists because the longer measurement interval allows more time for potentially significant changes to occur in the underlying population classification. If we treat the classification as fixed over the measurement interval, the perception of the sample with respect to the classification will be simplified. However, there will be no way to estimate trends such as changes in the proportion of area in each class. If part of the classification depends upon information gathered at a fixed point in time, such as a pre-cycle aerial photo interpretation, the expected value of the “true class” given the assumed or fixed class would show an increase in bias as time moves away from the time of the classification.

If we treat the classes as fixed yearly, the perception of the sample is complicated by the acknowledgement that each panel is potentially sampling a different underlying classification. The result is that the minimum area over which we make estimates

by class may have to be somewhat larger to ensure adequate sample sizes. The opportunity presented by the dilemma is the ability to account for changes occurring in the underlying classification during the measurement interval, at least over sufficiently large areas. At the same time, within class variance will be minimized because the “true” class will usually equal the assumed class.

NOTATION

Let

V_{ikt} = the value observed at plot i ($i = 1, \dots, I$), in class k , at time t

A_{ikt} = the area in acres of plot i sampled in class k at time t ,

$$C_{ikt} = \begin{cases} 1 & \text{If class } k \text{ occurs at plot } i \text{ (} i = 1, \dots, I \text{) and time } t \\ 0 & \text{Otherwise} \end{cases}$$

n_i = the number of plots within the arbitrarily selected boundary at time t

n_c = the number of classes

$$A_{i \cdot t} = \sum_{k=1}^{n_c} A_{ikt} \quad \text{= the area in acres sampled at plot } i \text{ (} i = 1, \dots, I \text{), and time } t,$$

$$n_{\cdot kt} = \sum_{i=1}^{n_i} C_{ikt}$$

$$A_{\cdot kt} = \sum_{i=1}^{n_i} A_{ikt}$$

$$V_{ikt} = \begin{cases} V_{ikt} / A_{ikt} & \text{If class } k \text{ occurs at plot } i \text{ and time } t, \\ 0 & \text{otherwise} \end{cases}$$

$$\bar{V}_{\cdot kt} = \sum_{i=1}^{n_i} A_{ikt} V_{ikt} / A_{\cdot kt} = \sum_{i=1}^{n_{kt}} V_{ikt} / \sum_{i=1}^{n_{kt}} A_{ikt} \quad , \text{ for sampled class } k.$$

INTERPRETATIONS OF THE MOVING AVERAGE

Suppose that the user's focus is on estimation of per acre value (V) and change in that value for each class k . However, for whatever reason, the original annual data are not available to the user. What is available to the user is the overall mean for the five-panel series, which is one estimator of per acre value (V) for class k

$$\hat{V}_{\cdot k \cdot} = \frac{1}{5} \sum_{t=h}^{h+4} \bar{V}_{\cdot kt}$$

Each year, new data are available for one of the five panels. The previous measurements for that panel are deleted from the estimator and the new measurements are incorporated (h is increased to $h+1$); therefore, the estimates are formed as a 5-year window moves through time, hence the term moving average.

Specifically, what does the moving average estimate with respect to time? Well, that depends upon the individual's viewpoint. We'll give three potential interpretations, each of which leads to a method of estimating change. Each of these methods could be used even if the annual data have not been provided and one has only the series of moving averages available.

One could assume that the moving average is providing an estimate of the center of the time interval (viewpoint 1). Alternatively, one could assume that the moving average is providing an estimate for the entire time interval (viewpoint 2). A third viewpoint is that the moving average is the mean of an unknown time-dependant linear combination, such as a simple linear trend (viewpoint 3).

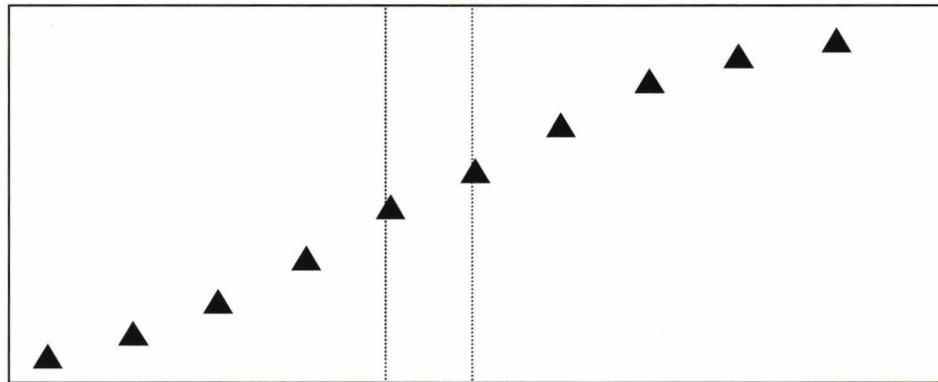
Viewpoint 1:

Considering viewpoint 1, illustrated in figure 2, the moving average is an unbiased estimator for the center year if there is either no trend in the variable of interest or if the trend is linear. We'll represent the moving average midpoint estimator as MM subscripted by the middle year, i.e., the mean of values for years 1995 through 1999 would be MM_{1995} so an estimator of change between two arbitrary years, say year 1 and year 2 would simply be

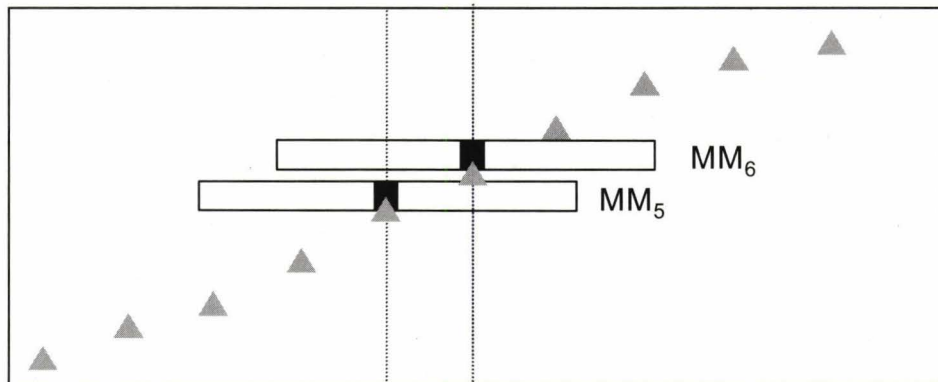
$$CM_{y_1 y_2} = MM_{y_2} - MM_{y_1}$$

Process for Viewpoint 1:

Step 1



Step 2



Step 3

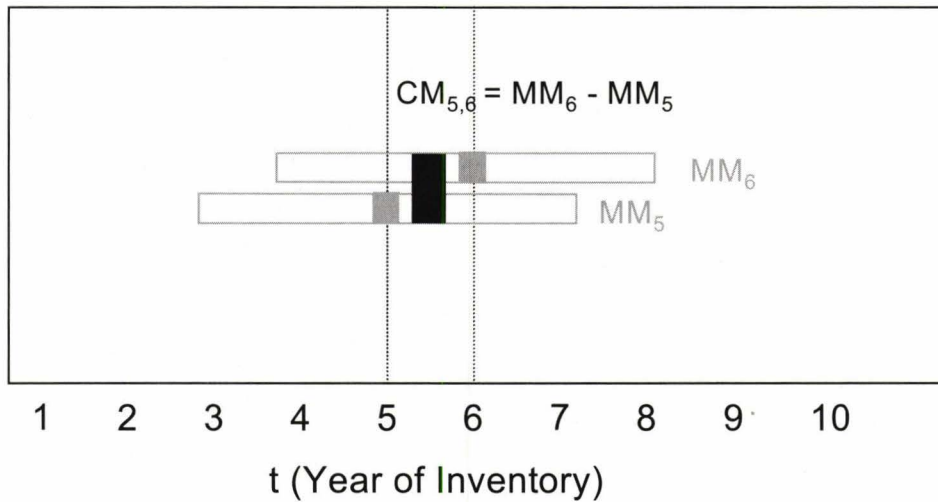


Figure 2.—Step 1 shows hypothetical means from the original data by year. Step 2 shows the years over which two moving averages were made (empty rectangle), while the dark squares represent the interpretation of the moving average as an estimator of the midpoint of the time interval. Step 3 depicts change as the difference between the two midpoint estimators.

The major drawback to MM_Y as an estimator is that it cannot be shown to be unbiased in the presence of any trend other than a simple linear trend. However, the change estimator $CM_{Y_1Y_2}$ will be unbiased whenever the bias in MM_Y is zero or constant. A disadvantage to $CM_{Y_1Y_2}$ is that the first year of interest would need to be after the second year of data collection and at least 2 years of data must be collected after the final year of interest.

Viewpoint 2:

Given viewpoint 2, illustrated in figure 3, the moving average is an unbiased estimator for the interval mean over a restricted set of trend assumptions. We'll represent the moving average interval estimator as MI subscripted by the first and last year of the interval, i.e., the mean of values for years 1995 through 1999 would be $MI_{1995,1999}$. To form annual estimates, we note that eventually, for a particular year of interest (y), there would be five interval estimates that cover the year, $MI_{y-4,y}$, $MI_{y-3,y+1}$, $MI_{y-2,y+2}$, $MI_{y-1,y+3}$, and $MI_{y,y+4}$. An estimator for year y could be formed by taking the mean of these five interval estimates

$$MA_y = \frac{1}{5} \sum_{i=4}^0 MI_{y-i,y-4+i}$$

The change estimate is found through subtraction

$$CA_{Y_1Y_2} = MA_{Y_2} - MA_{Y_1}$$

The largest drawback to using $CA_{Y_1Y_2}$ is that the first year of interest would need to be greater than the fourth year of data collection and at least 4 years of data must be collected after the final year of interest. This is not an absolute restriction, since adaptation of the estimator to fewer than five available intervals is trivial.

Viewpoint 3:

With viewpoint 3, one has a route to annual estimates as soon as the second average has been obtained using a difference estimator. We give an illustration of this viewpoint in figure 4. We'll represent the moving average linear estimator as ML subscripted by the first and last year of the interval, i.e., the mean of values for years 1995 through 1999 would be $ML_{1995,1999}$. To form annual estimates, we note that the difference, $d_t = ML_{t+1,t+5} - ML_{t,t+4}$, under a simple linear model leads to an immediate series of annual estimates:

$$ML_{t+1,t+5} = ML_{t,t+4} + d_t$$

$$\sum_{i=t+1}^{t+5} \frac{AL_i}{5} = \sum_{i=t}^{t+4} \frac{AL_i}{5} + d_t$$

$$\left(\sum_{i=t+1}^{t+4} \frac{AL_i}{5} \right) + \frac{AL_{t+5}}{5} = \frac{AL_t}{5} + \left(\sum_{i=t+1}^{t+4} \frac{AL_i}{5} \right) + d_t$$

$$\frac{AL_{t+5}}{5} = \frac{AL_t}{5} + d_t$$

$$AL_{t+5} = AL_t + 5d_t \therefore$$

$$AL_{t+4} = AL_t + 4d_t$$

$$AL_{t+3} = AL_t + 3d_t$$

$$AL_{t+2} = AL_t + 2d_t$$

$$AL_{t+1} = AL_t + 1d_t$$

$$AL_t = AL_t + 0d_t$$

To start the recursive series, we need the annual estimator AL_t in terms of $ML_{t,t+4}$

$$ML_{t,t+4} = ML_{t+1,t+5} - d_t$$

$$ML_{t,t+4} = \frac{AL_{t+1} + AL_{t+2} + AL_{t+3} + AL_{t+4} + AL_{t+5}}{5} - d_t$$

$$ML_{t,t+4} = \frac{AL_t + d_t + AL_t + 2d_t + AL_t + 3d_t + AL_t + 4d_t + AL_t + 5d_t}{5} - d_t$$

$$ML_{t,t+4} = AL_t + 2d_t$$

$$AL_t = ML_{t,t+4} - 2d_t$$

A linear predictor is available for any successive year h , $AL_{t+h} = AL_t + hd_t$. Therefore, the change estimator between any two years t and $t+h$

$$CL_{t+h,h} = AL_{t+h} - AL_t = hd_t$$

The development above gives us a prior prediction for year $t+6$

$$AL_{t+6} = AL_t + 6d_t$$

Another estimate for time $t+6$ can be found once the estimator $ML_{t+2,t+6}$ is available by reapplying the above logic

Process for Viewpoint 2:

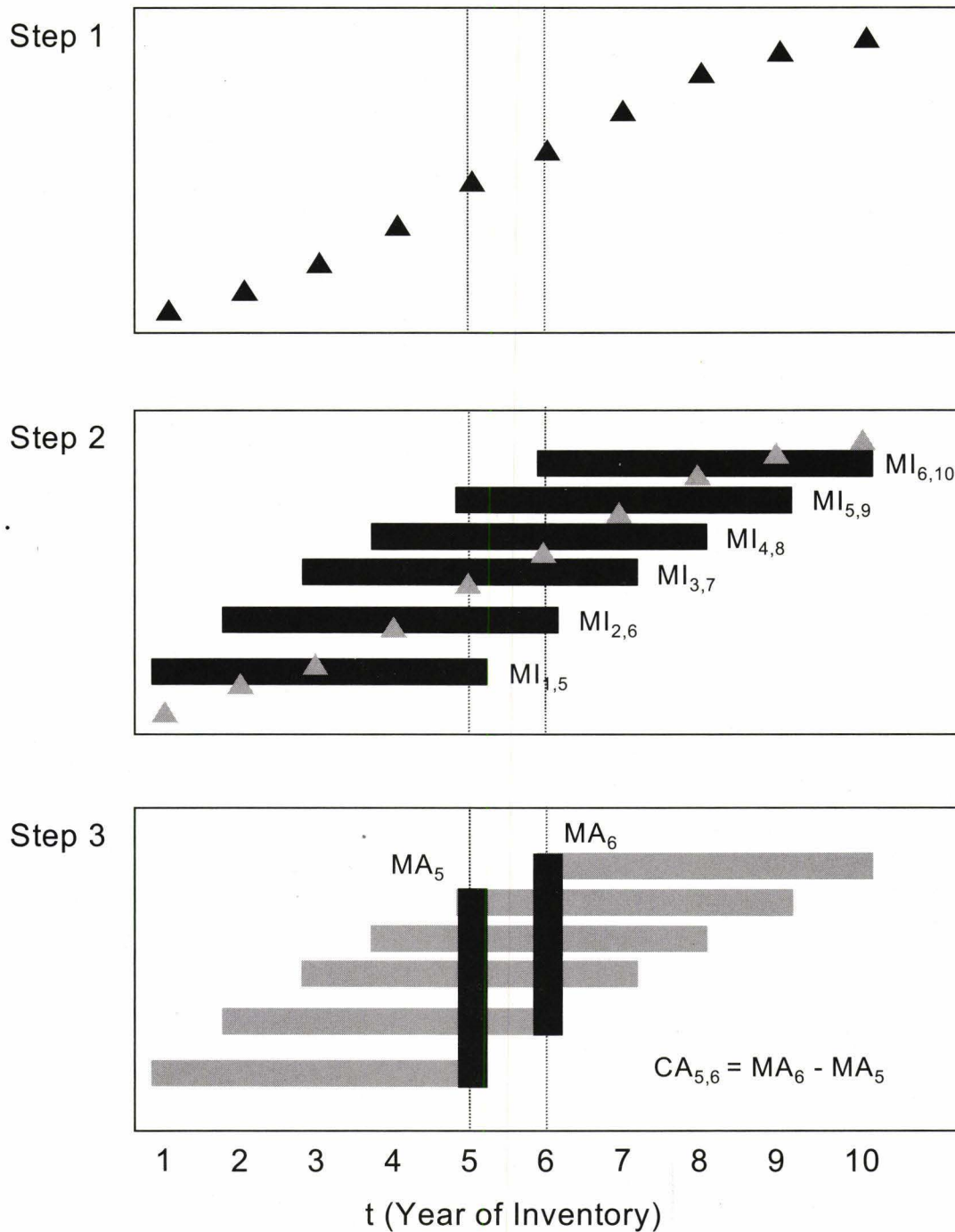


Figure 3.—As in figure 2, step 1 shows hypothetical means from the original data by year. Step 2 shows the years over which six moving averages were made (filled rectangles), with the interpretation of the moving average as an estimator of the interval. Step 3 depicts the means of all five intervals covering each of the same 2 years of interest shown in figure 2. Change is given as the difference between the two mean of intervals estimators.

Process for Viewpoint 3:

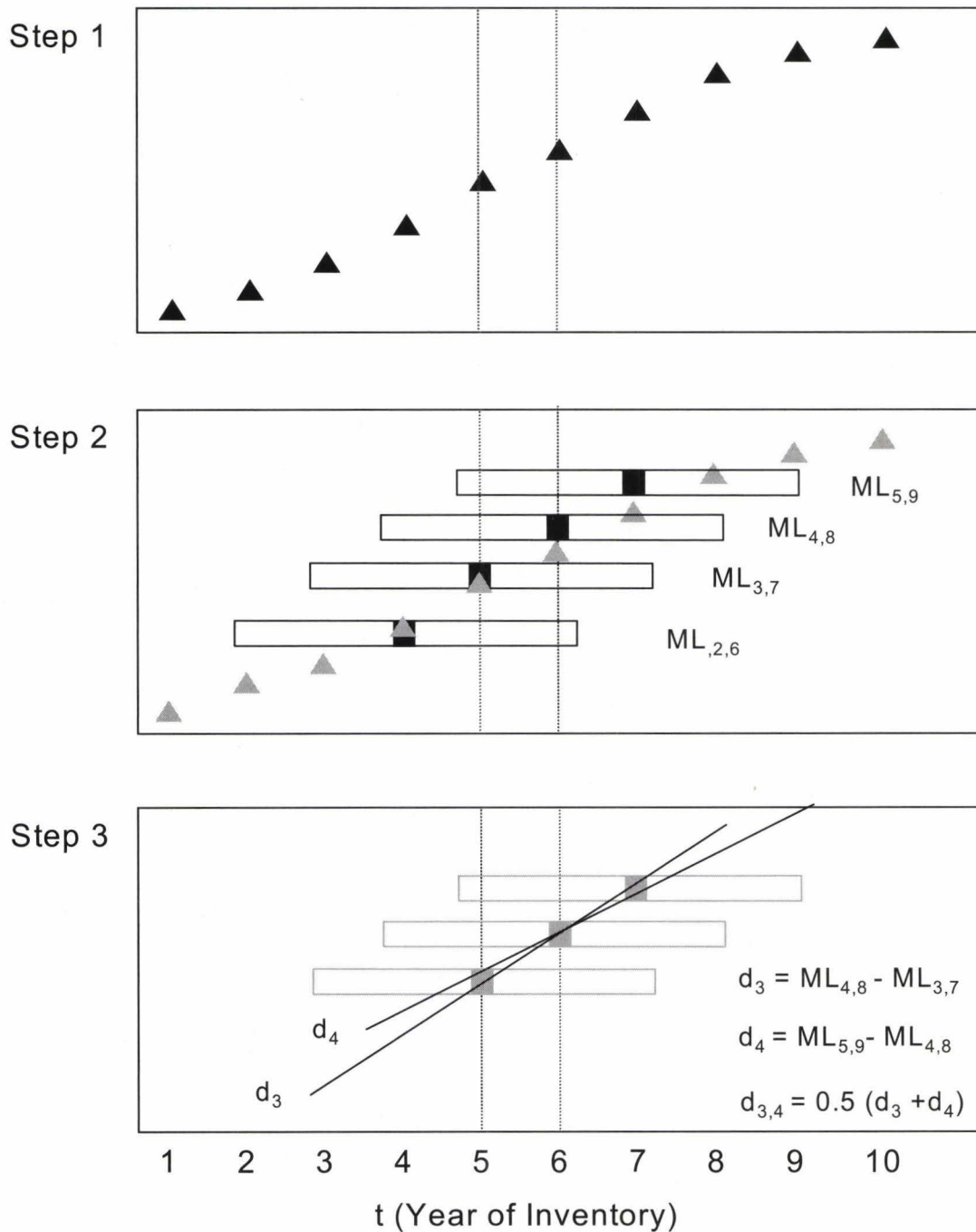


Figure 4.—As in figures 2 and 3, step 1 shows hypothetical means from the original data by year. Step 2 shows the years over which four moving averages were made (empty rectangles), with a point representing the average arbitrarily shown at the center of the interval (solid square). The interpretation is that each moving average is the result of an unknown linear combination, which depends upon year of measurement. Step 3 depicts two estimates of the trend found by taking the difference between successive moving averages. Finally, a mean trend is shown as the average of two successive trends.

$$ML_{t+2,t+6} = ML_{t+1,t+5} + d_{t+1}$$

$$\sum_{i=t+2}^{t+6} \frac{AL_i}{5} = \sum_{i=t+1}^{t+5} \frac{AL_i}{5} + d_{t+1}$$

$$\left(\sum_{i=t+2}^{t+5} \frac{AL_i}{5} \right) + \frac{AL_{t+6}}{5} = \frac{AL_{t+1}}{5} + \left(\sum_{i=t+2}^{t+5} \frac{AL_i}{5} \right) + d_{t+1}$$

$$\frac{AL_{t+6}}{5} = \frac{AL_{t+1}}{5} + d_{t+1}$$

$$AL_{t+6} = AL_{t+1} + 5d_{t+1}$$

$$AL_{t+6} = AL_{t+1} + 5d_{t+1} \therefore$$

$$AL_{t+5} = AL_{t+1} + 4d_{t+1}$$

$$AL_{t+4} = AL_{t+1} + 3d_{t+1}$$

$$AL_{t+3} = AL_{t+1} + 2d_{t+1}$$

$$AL_{t+2} = AL_{t+1} + 1d_{t+1}$$

$$AL_{t+1} = AL_{t+1} + 0d_{t+1}$$

Noting that similar to the above, we can find the start point

$$AL_{t+1} = ML_{t+1,t+5} - 2d_{t+1}$$

Then

$$AL_{t+1} = ML_{t+1,t+5} - 2d_{t+1}$$

$$AL_{t+2} = ML_{t+1,t+5} - d_{t+1}$$

$$AL_{t+3} = ML_{t+1,t+5}$$

$$AL_{t+4} = ML_{t+1,t+5} + d_{t+1}$$

$$AL_{t+5} = ML_{t+1,t+5} + 2d_{t+1}$$

$$AL_{t+6} = ML_{t+1,t+5} + 3d_{t+1}$$

Setting the two estimates for AL_{t+6} equal

$$AL_{t+6} \Rightarrow ML_{t,t+4} + 4d_t \equiv ML_{t+1,t+5} + 3d_{t+1}$$

$$\Rightarrow ML_{t+1,t+5} + 3d_t \equiv ML_{t+1,t+5} + 3d_{t+1}$$

$$\Rightarrow d_t \equiv d_{t+1}$$

If $d_t \neq d_{t+1}$, an adjustment to the linear model is suggested.

Retaining the linearity assumption, we could use the mean slope

$\bar{d}_{t,t+1} = .5(d_t + d_{t+1})$, and the mean midpoint

$$\overline{ML}_{t+1,t+5} = \frac{1}{3}(ML_{t,t+4} + ML_{t+1,t+5} + ML_{t+2,t+6})$$

to obtain new estimates for each year

$$\overline{AL}_t^{t,t+1} = \overline{ML}_{t+1,t+5} - 3\bar{d}_{t,t+1}$$

$$\overline{AL}_{t+1}^{t,t+1} = \overline{ML}_{t+1,t+5} - 2\bar{d}_{t,t+1}$$

$$\overline{AL}_{t+2}^{t,t+1} = \overline{ML}_{t+1,t+5} - \bar{d}_{t,t+1}$$

$$\overline{AL}_{t+3}^{t,t+1} = \overline{ML}_{t+1,t+5}$$

$$\overline{AL}_{t+4}^{t,t+1} = \overline{ML}_{t+1,t+5} + \bar{d}_{t,t+1}$$

$$\overline{AL}_{t+5}^{t,t+1} = \overline{ML}_{t+1,t+5} + 2\bar{d}_{t,t+1}$$

$$\overline{AL}_{t+6}^{t,t+1} = \overline{ML}_{t+1,t+5} + 3\bar{d}_{t,t+1}$$

This crude but effective approach could be reapplied as each successive year's average became available.

Again, the change estimate is found through subtraction

$$CL_{Y_1,Y_2} = \overline{AL}_{Y_2}^{t,t+k} - \overline{AL}_{Y_1}^{t,t+k}$$

The advantage of viewpoint 3 over viewpoint 2 is that the first year of interest could be the first year that data are collected, as long as 6 years of data have been collected, and the final year of interest could be the final year of data collection. The major disadvantage is the potential of a poor fit to other than simple linear trends.

NUMERICAL EXAMPLE

In figures 5 and 6, we present a numerical example that illustrates estimates of softwood volume per acre in planted stands. Although the data are contrived, the range of observations could realistically be expected in an area such as southeast Georgia. The values in figure 5 are estimates from successive 5-year intervals, analogous to the horizontal bars in figures 2 through 4. Figure 6 illustrates the mean trend of viewpoint 3 for the data in figure 5 compared to the individual annual estimates.

CONCLUSION

The development above is intended to shed some light on the potential effects of providing moving average estimates. On the one hand, we have a sample design spread uniformly through time and space, and this design provides adequate data to make estimates over domains of interest every 5 years. On the other hand, we expect that many users will be interested in uniquely

Year	Softwood Volume	5-Year Moving Average	Viewpoint 1- Moving average as a Midpoint Estimator			Viewpoint 2- Moving average as an Interval Estimator			Mean of Covering Intervals	
1	1570.0									
2	1459.6									
3	1501.2									
4	1350.6									
5	1503.5	1477.0	MM ₃	1477.0	Change Estimator	MI _{1,5}	1477.0			
6	1401.2	1443.2	MM ₄	1443.2	CM _{3,4}	MI _{2,6}	1443.2			
7	1399.3	1431.2	MM ₅	1431.2	CM _{4,5}	MI _{3,7}	1431.2	MA ₅	1441.0	
8	1461.4	1423.2	MM ₆	1423.2	CM _{5,6}	MI _{4,8}	1423.2	MA ₆	1430.3	
9	1385.6	1430.2	MM ₇	1430.2	CM _{6,7}	MI _{5,9}	1430.2			
10	1470.5	1423.6	MM ₈	1423.6	CM _{7,8}	MI _{6,10}	1423.6			

Year	Softwood Volume	5-Year Moving Average	Viewpoint 3- Moving average as a General Linear combination			First Two Available		Second and Third		Combined	
1	1570.0					AL ₁	1544.5	Predict AL ₁ ²	1479.4	AL ₁ ^{1,2}	1519.18
2	1459.6					AL ₂	1510.7	AL ₂ ²	1467.3	AL ₂ ^{1,2}	1496.27
3	1501.2		ML _{1,5}	1477.0		AL ₃	1477.0	AL ₃ ²	1455.3	AL ₃ ^{1,2}	1473.36
4	1350.6		ML _{2,6}	1443.2	d ₁	AL ₄	1443.2	AL ₄ ²	1443.2	AL ₄ ^{1,2}	1450.45
5	1503.5	1477.0	ML _{3,7}	1431.2	d ₂	AL ₅	1409.5	AL ₅ ²	1431.2	AL ₅ ^{1,2}	1427.54
6	1401.2	1443.2	ML _{4,8}	1423.2	d ₃	AL ₆	1375.7	AL ₆ ²	1419.1	AL ₆ ^{1,2}	1404.63
7	1399.3	1431.2	ML _{5,9}	1430.2	d ₄	Predict AL ₇	1341.9	AL ₇ ²	1407.0	AL ₇ ^{1,2}	1381.72
8	1461.4	1423.2	ML _{6,10}	1423.6	d ₅						
9	1385.6	1430.2						~d _{1,2}	-22.91		
10	1470.5	1423.6						~ML _{2,6}	1450.45		

Figure 5.—Estimates formed from each of the three viewpoints.

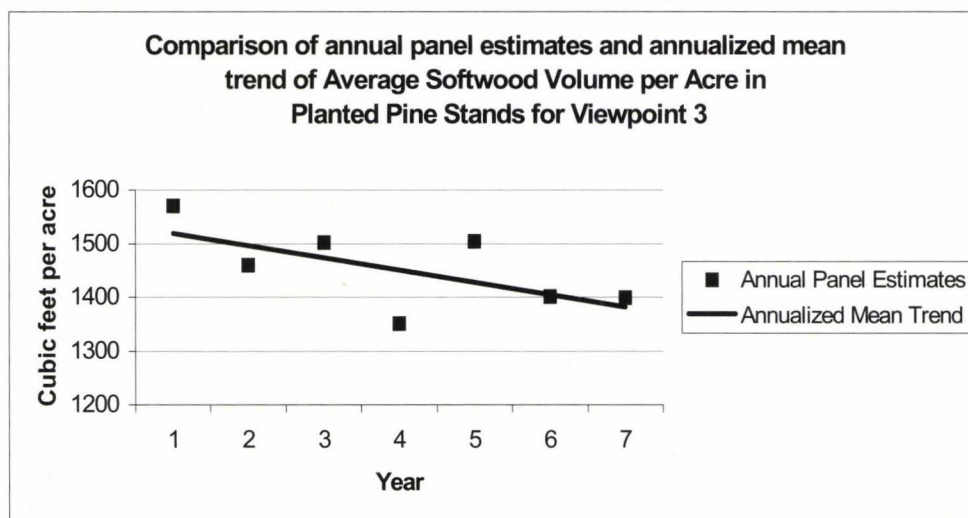


Figure 6.—The mean trend plotted for the data in figure 5.

defined subareas and time intervals. Specifically, many users will expect annual estimates. For users with the wherewithal to analyze the raw data, we could simply provide the raw data. Users could then choose to model the time trend if they so desire. Van Deusen (in review) presents a mixed estimator that can incorporate increasing levels of constraints on the derivatives of the time trend, allowing one to model various levels of complexity in the time trend. Roesch (2001) discusses this and other approaches in the simpler context of a single panel series. However, many users would rather obtain the information in some reduced form. Because of the wide variety of variables that we report on, it would be

difficult to identify a single temporal model that would be applicable to all variables of interest. This has resulted in an internal agreement to use the moving average when a specific temporal model has not been identified.

In this paper, we discussed three methods for interpreting the moving average over arbitrary intervals of space and time from the annual FIA design. These are not the estimators that FIA will use in its processing system for standard estimates. Over the next few years, FIA will be evaluating models of varying complexity for all variables of interest in an effort to determine the most efficient approach for each variable.

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ISSUES RELATED TO PANEL CREEP

Paul C. Van Deusen¹

ABSTRACT.—The annual inventory system was designed under the assumption that a fixed percentage of plots would be measured annually in each State. The initial plan was to assign plots to panels to provide systematic coverage of a State. One panel would be measured each year to allow for annual updates of each State using simple estimation procedures. The reality is that fluctuating budgets don't always permit a panel to be finished before the end of the field season. Therefore, sections of the State are left unmeasured, and State-level estimates can't be updated until the panel is completed. Creating extra panels is one way to reduce the impact of taking more than 1 year to measure a panel.

The annual inventory system, as mandated by the 1998 Farm Bill, was motivated by the public's desire to have a nationwide forest inventory system that could provide an annual update of each State's forests. The Farm Bill required an equal percentage of plots to be measured annually in each State. FIA provided for this requirement by dividing each State into panels consisting of subsets of plots that systematically cover the State. The panel system is an elegantly simple mechanism for obtaining annual estimates when one panel is measured each year. Annual estimates can be obtained by using individual panels or by combining the current panel with earlier ones.

FIA created 5 panels in the East and 10 panels in the West with the intention of measuring 20 percent and 10 percent of the plots in those respective regions. The reality is that uncertain budgets don't allow a rigid panel system to work as designed. FIA personnel have coined the term "panel creep" to describe panels that are only partially measured at the end of the field season. FIA has enough funding in the East to measure one-seventh of the plots per year, and panel creep will be avoided only in States that can "buy up" to 20 percent per year, such as Maine. As panel measurements creep into a second year, the Farm Bill vision of an annual inventory begins to fade.

REVIEW OF DESIGN ALTERNATIVES

When the annual inventory was being planned, a number of design alternatives were considered. A brief review of some of

those alternatives is given to remind the reader why the panel system was chosen. This is followed by a discussion of modifications that make the interpenetrating panel design more flexible. The periodic design will be discussed because it was in place before the annual system. The concentrated grid design is discussed because it is an alternative way to take annual estimates. There is also some discussion of a disturbance design that was tested for implementing a different approach to the annual inventory in the Lake States.

Periodic Design

The periodic design was based on the premise that State-level estimates were important and that precision at a single point in time was the primary measure of quality. This led to the measurement of all the plots in a State over the course of 1 or more years and then remeasurement at approximately 10-year intervals. The remeasurement interval crept up to 15 years in some States (e.g., Maine) leaving an information gap that was unacceptable to many users. The call from users for timely data was documented in the first Blue Ribbon Panel (BRP I) report (American Forest Council 1992) and in BRP II (American Forest and Paper Association 1998). BRP I did not call for dismantling the periodic design, but requested reduction of the survey cycle from 10 years to 5 years. BRP II concluded that FIA should move to an annual system that would measure 20 percent of the plots in a State annually. This call for a drastic change in the system resulted from the periodic design's failure to produce more timely data.

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Concentrated Grid Design

The concentrated grid design was proposed as a compromise between the interpenetrating and periodic designs. An equal portion of the plots would be measured each year by dividing each State into concentrated zones. In this way, there would be annual measurements taking place in each State, but each within-State zone would be under a periodic survey. This design is very similar to the periodic design, which divided States into survey units that were usually measured one at a time. Some would argue that it also meets the Farm Bill requirements, even though it doesn't allow for annual statewide estimates. The concentrated grid design might also allow for reduced travel costs relative to the interpenetrating design. However, the concentrated grid design would make it difficult to produce State-level reports, because plots in different parts of the State are measured in different years.

Disturbance Design

The disturbance sampling design was developed for the Annual Forest Inventory System (AFIS) pilot study in the Lake States, which began in 1992. This design allocates sampling effort to plots with probability proportional to disturbance. The design called for measuring all disturbed plots each year and then taking a random or systematic sample of undisturbed plots. Disturbance would be detected via remote sensing. This design would be very good for determining the amount and impact of disturbance, but it leads to more complicated analysis options than either the interpenetrating or periodic designs. Any analysis would have to differentiate between plots that were measured because they were disturbed versus the randomly chosen undisturbed plots. Proponents felt that the disturbance design could be more economical to implement than a rigid interpenetrating design where 20 percent of the plots are measured each year. However, the disproportionate weighting of disturbed plots made the design appear to be too timber oriented, which was an argument against it.

Interpenetrating Design

The interpenetrating design was originally developed for the Southern Annual Forest Inventory System (SAFIS) pilot study, which began in 1995. This design is similar to the National Forest Health Monitoring design and calls for annual measurement of panels that consist of plots that systematically

cover the region of interest. This design appealed to many Southern State foresters who consequently supported SAFIS. The interpenetrating design made SAFIS somewhat compatible with the original annual forest inventory (AFIS) pilot study that began in the Lake States in 1992. The use of different designs for AFIS and SAFIS gave FIA the opportunity to study two alternative ways of "going annual."

The interpenetrating design is compatible with a number of estimators, because each panel provides systematic coverage of the State. Therefore, a single panel can be used to provide an estimate for a State by simply computing the mean and variance from individual per acre plot measurements. Likewise, several panels can be combined to provide estimates with increased precision. The interpenetrating design supports simple estimators but doesn't preclude more complex approaches that might increase precision.

ESTIMATORS

The focus here is on the 5-year moving average, because this has been chosen by FIA to be the default estimator for the annual inventory system. The discussion centers on some theoretical aspects of the moving average and how it is impacted by panel creep. A mixed estimation alternative to the moving average is also considered, because it has some advantages that justify its added complexity. The effect of panel creep on these estimators is also discussed.

Moving Average

The moving average is easy to apply and will work under the interpenetrating panel design (Roesch and Reams 1999). Consider first how the moving average works under an ideal scenario where one of five panels is measured each year. FIA plans to produce estimates using 5 years or panels worth of data. For years $t-4$ through t , this can be written as

$$MA_{t-4,t} = \sum_{j=t-4}^t w_j \bar{y}_j$$

where

$$\bar{y}_j$$

is the average of all plot values measured in year j , and w_j is a weight such that $\sum w_j = 1$. The weight, w_j , ensures that each panel is weighted according to the proportion of the total plots it contains. With an exact 20 percent sample, $w_j = 0.2$.

The panel mean is unbiased for the true underlying value, β_t , and we can write

$$\bar{y}_t = \beta_t + e_t$$

where e_t is a random error term. It follows that the expected value of the moving average is

$$E(MA_{t-4,t}) = \sum_{j=t-4}^t w_j \beta_j$$

Therefore, $MA_{t-4,t}$ estimates the weighted average over the last 5 years and is not an unbiased estimate of the value at any particular time. This is similar to what was done under the old periodic survey. It often took 3 or more years to complete the full periodic survey in a State, and State estimates were obtained by averaging all plots together as if they had been measured in the same year.

The variance of the moving average is easy to derive as

$$V(MA_{t-4,t}) = \sum_{j=t-4}^t w_j^2 V(\bar{y}_j)$$

where $V(\bar{y}_j) = \sigma_j^2 / n_j$, σ_j^2 is estimated from the between-plot variance within the panel and n_j is the number of plots in the panel measured in year j .

Change is at least as important as current status to most users of FIA data. FIA has promised to provide change estimates between 5-year time intervals, but many users will want to look at annual change estimates. The following equation shows the difference between the 5-year moving averages at year 6 and year 5 assuming that each panel contained 20 percent of the plots.

$$\begin{aligned} MA_{2,6} - MA_{1,5} &= \frac{1}{5} \{ (\bar{y}_2 + \bar{y}_3 + \bar{y}_4 + \bar{y}_5 + \bar{y}_6) - (\bar{y}_1 + \bar{y}_2 + \bar{y}_3 + \bar{y}_4 + \bar{y}_5) \} \\ &= \frac{1}{5} (\bar{y}_6 - \bar{y}_1) \end{aligned}$$

The final estimate is shown to consist of the difference between measurements in year 6 and year 1, all divided by 5. Since we are still looking at the ideal scenario where the same panel is remeasured after 5 years, the year 6 measurements and the year 1 measurements come from the same panel. In other words, annual change from the moving average estimator is estimated from the 5 year change in the current panel, and the other four panels are ignored. This is a valid approach but does not use the data efficiently.

The moving average can still work with panel creep. However, a panel should not be incorporated onto the moving average until it is completely measured. This is important because the plots were assigned to panels to provide systematic coverage of a State. Therefore, a partially measured panel is likely to systematically exclude a section of the State and would lead to a biased estimate. Panel creep also means that the moving average after 5 years might consist of only 60 or 80 percent of the plots in a State. Also, the moving average loses some simplicity with panel creep, since the measurement year of the plots within a panel can now vary.

Mixed Estimator

Mixed estimation (Theil 1971) is analogous to Bayes methods in that it includes some prior information that influences the final results. It is more complicated than the moving average, but it provides model-unbiased estimates of current status, change estimates over any time interval, and variance estimates. Numerous variations that can be considered (Van Deusen 1996, 1999a), but only a single promising variant is presented here.

A mixed estimator is defined by an observation equation and a transition equation, where the transition equation is analogous to the Bayesian prior distribution. Therefore, mixed estimation

is a cross between Bayesian and frequentist approaches. The observation equation used here is

$$y_t = \beta_t + e_t$$

where e_t is an independent random error with mean 0 and variance σ_t^2/n_t . A sensible transition equation is

$$\beta_t - 2\beta_{t-1} + \beta_{t-2} = v_t$$

where v_t is an independent random error with $p\sigma_t^2/n_t$ variance and p is a parameter that is estimated from the data. The uncertainty associated with the transition equation increases with p , which diminishes the influence of the transition equation. As p goes to infinity, the mixed estimator would approach the mean for each panel assuming no panel creep. The transition equation provides some linkage between current values and those preceding it. This smoothing effect makes sense, since most forest statistics will tend to change little from one year to the next.

The estimation process is best described using matrix notation. The equations stay the same regardless of how much data are used, and the estimates will usually improve with more data. Therefore, there is no reason to use only the most recent 5 years of data. The matrix estimation equations for years 1 through T are

$$\hat{\beta} = \left[\Sigma^{-1} + \frac{1}{p} R' \Omega^{-1} R \right]^{-1} \Sigma^{-1} Y, \text{ and}$$

$$V(\hat{\beta}) = \left[\Sigma^{-1} + \frac{1}{p} R' \Omega^{-1} R \right]^{-1},$$

where,

$$\hat{\beta} = [\beta_1, \beta_2, \dots, \beta_T], \quad \Sigma^{-1} = \text{DIAG}(\sigma_1^2/n_1, \sigma_2^2/n_2, \dots, \sigma_T^2/n_T)$$

, R is used to implement the selected transition equation, Ω contains transition variances on the diagonal, and

$Y = [y_1, y_2, \dots, y_T]$. More details can be found in Van Deusen (1999).

These are relatively simple equations that provide all required estimates. For example, to estimate the change from time $t-k$ to t simply use $\hat{\beta}_t - \hat{\beta}_{t-k}$. A complete covariance-matrix is available, which makes it possible to estimate the variance of change. Thus, mixed estimators provide very general capabilities for estimating status and trend.

Mixed estimators will work with panel creep, but are subject to the same constraint as the moving average on using only fully measured panels. The estimation equations remain essentially the same with panel creep, but the direct correspondence between measurement year and panel is lost. The means in $\hat{Y}$ would be estimated only from that portion of a panel that was measured in the appropriate year.

DESIGN MODIFICATIONS

The only way to avoid panel creep would be to have adequate resources, which can't be assured. Budgets might be inadequate or field crew personnel might leave unexpectedly. However, there are design modifications that could lessen the impact. The most obvious is to create extra panels or subpanels (Van Deusen 1999b). Another approach would be to sequence the measurement of plots within a panel in such a way that near systematic coverage would be maintained even in the presence of panel creep. This would allow the panel measurements to be included even though some plots aren't measured yet.

Creating Subpanels

Creating subpanels or extra panels has two advantages: 1) panel creep is less likely to occur with smaller panels and 2) the impact is less when panel creep does occur. Suppose there were 20 panels in all States, with each panel providing near systematic coverage of a State. It would be possible to measure four panels per year to get 20 percent or two panels to get 10 percent of the plots per year. A reduced budget could be accommodated in the East by measuring three instead of four panels, while a budget increase might allow five panels. Panel creep is less likely to occur because each panel now contains only 5 percent of the plots, and it should be easier to ensure that a panel is completed before the end of a field season. An incompletely measured panel should still not be used for estimation purposes, but this means that less than 5 percent of the plots are withheld as opposed to almost 20 percent under a five-panel system.

The plan for the East is to measure some States over 7 years and others over 5 years, which suggests that 35 panels be created to accommodate both options. This certainly can be done, but each panel would contain less than 3 percent of the plots. There is a point at which panels contain so few plots as to be logistically unacceptable. If we agree that some amount of panel creep is inevitable, then the issue is best framed around a

tolerable percentage of plots that could be potentially withheld due to panel creep. For example, a five-panel system might lead to nearly 20 percent of the plots being measured, but unavailable for estimation purposes until after the next field season when the panel is completed. A 20-panel system should have no more than 5 percent of plots withheld, and a 35-panel system should result in no more than 3 percent withheld.

A 20-panel system would seem to be a reasonable goal. It accommodates 5- or 10-year cycles evenly, but doesn't quite work for a 7-year cycle. However, there is no guarantee that any number of panels would eliminate panel creep. If we manage to measure 21 panels over 7 years, then an extra 5 percent of the plots are measured: with 19 panels in 7 years, we have a 5-percent shortfall. A 20-panel system might be a reasonable compromise between having large travel times among plots in the same panel and minimizing the chance that a panel is partially finished at the end of the year.

Some logistical issues are associated with smaller panels. Plots are far apart in small panels, so several panels should be measured concurrently to minimize travel time. This could lead to having several small, yet incomplete panels at the end of a field season. This could be avoided by stopping work on one of the panels when it becomes clear that resources are insufficient to finish all panels.

CONCLUSIONS

FIA plots have been assigned to panels in such a way that each panel contains about the same number of plots and provides systematic coverage of a State. FIA created 5 panels in the East and 10 in the West. The annual forest inventory system was originally designed on the assumption that one panel would be measured each year in each State. Panel creep occurs when the field season ends before a panel is completed.

The down side to panel creep is that the entire panel should be excluded from State-level estimates until it is completely measured. This is because a section of the State is likely to be systematically underrepresented if partial panels are used in the estimation process, which could lead to biased estimates. With a five-panel system, this means that 20 percent of the plots are unavailable until the panel is completed. Panel creep therefore has a detrimental impact on the annual

nature of the inventory. Even though measurements are taken annually, it may not be possible to provide annual updates when panel creep occurs.

This problem could be ameliorated by creating extra panels so that each panel contains fewer plots but still provides systematic coverage. This lessens the chance that panel creep will occur and reduces the number of measured plots that are unusable when it does occur. Panel creep has been inadvertently built into the system in the East by creating five panels per State when the FIA budget would only support measuring some States over a 7-year period. Therefore, it seems that the number of panels should be increased to at least match the expected measurement cycles throughout the country. Creating enough extra panels to accommodate budget fluctuations seems to have a number of pros and few cons.

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COMPARING MINNESOTA LAND COVER/USE AREA ESTIMATES USING NRI AND FIA DATA

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ABSTRACT.—Areas for land cover/use categories on non-Federal land in Minnesota were estimated from Forest Inventory and Analysis (FIA) data and National Resources Inventory (NRI) data. Six common land cover/use categories were defined, and the NRI and FIA land cover/use categories were assigned to them. Area estimates for these categories were calculated from the FIA and NRI data and compared. Differences were found between FIA and NRI area estimates for all land cover/use categories.

The Forest Service (FS) and Natural Resources Conservation Service (NRCS) are both agencies within the United States Department of Agriculture (USDA), and each conducts a national inventory. The FS Forest Inventory and Analysis (FIA) program conducts surveys of all land in the United States to monitor the status, trends, and health of our Nation's forests. The NRCS conducts the National Resources Inventory (NRI) on all non-Federal land to monitor the status, condition, and trends of our Nation's soil, water, and related resources. These national inventories often overlap in types of estimates produced and geographic areas over which the estimates are made. Yet, resource area estimates produced by the two agencies do not always agree. A demonstration project in north central Oregon examined FIA and NRI area estimates by constructing a common sampling frame for the two inventories (Goebel and others 1998). In this study we used the existing FIA and NRI sampling designs with FIA data from the 1977 and 1990 periodic inventories and the 1999 annual inventory and the 1997 NRI data for the years 1982, 1987, 1992, and 1997 to explore estimation differences in Minnesota. The objectives of this study were to 1) define common land cover/use categories, 2) crosswalk NRI and FIA land cover/use categories, and 3) compare land cover/use area estimates obtained from FIA and NRI data.

LAND COVER/USE CATEGORIES

The Forest Inventory and Analysis (FIA) and National Resources Inventory (NRI) programs differ in many of their land cover/use classifications. Because these classifications are generally not one-to-one matches, we chose to combine land cover/use into six major classifications for area estimate comparison: forest land, cropland/pastureland, other rural land, developed land, small water areas, and Census water (table 1). Although the categories used in this paper have been generalized, assignment problems still arise because of differences in definitions between the two inventories.

The first land cover/use category, forest land, is defined by FIA as land that is currently at least 10 percent stocked with live trees of any size that are expected to reach a height of at least 12 feet at maturity or land that has been at least 10 percent stocked in the past and not currently developed for nonforest use. Forest land is not subject to nonforest uses that prevent normal tree regeneration and succession such as regular mowing or intensive grazing. To qualify as FIA forest land, the area must be at least 1 acre in size and have a minimum width of 120 feet (FIA Field Methods for Phase 2 Measurements, 2001, <http://fia.fs.fed.us/library.htm#Manuals>). The NRI defines forest land as land that is at least 10 percent stocked by trees of any size that will be at least 4 m (13 ft) tall at maturity. Also included in forest land is land bearing evidence of natural regeneration of tree cover (cutover forest or abandoned farmland) and not currently developed for nonforest use. The minimum area for classification of NRI forest land is 1 acre, and the area must be at least 100 feet wide (1997 NRI Data Collection Instructions, http://www.nrcs.usda.gov/technical/NRI/1997/data_gathering.html). Although similar in many ways, there are several differences between FIA and NRI forest

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Table 1.—FIA and NRI non-Federal land cover/use categories combined for the six general categories: forest land, cropland/pastureland, other rural land, developed land, Census water, and non-census water

Combined category	FIA Code	Description	NRI Code	Description
Forest land	20	Timberland	341	Forest, grazed
	21	Pastured timberland	342	Forest, not grazed
	22	Plantations		
	40	Unproductive forest land		
	41, 45	Reserved forest land		
	57	Wide windbreaks		
	59	Wooded pasture		
Cropland/pastureland	51	Cropland with trees (orchards)	1-6	Horticulture crops
	52	Pasture with trees	11-20	Row crops
	54	Idle farmland with trees	21-116	Close grown crops
	61	Cropland without trees	141-143	Hayland
	62	Pasture without trees	170-180	Other cropland
	64	Idle farmland without trees	211-213	Pasture
			410	CRP
Other rural land	46	Christmas tree plantations	400	Farmsteads
	50	Reserved non-forest with trees	401	Other land in farms
	53	Wooded strip	611, 612	Salt flats, bare rock
	56	Narrow windbreaks	614, 615	Beaches and dunes
	58	Shelterbelt	616	Mixed barren land
	65	Marsh without trees	617, 618	Mud flats, river wash
	66	Other farmland and farmsteads	620	Other barren land
	69	Reserved non-forest	640	Marshland
		without trees	650	All other land
Developed land	67	Urban and other areas	613	Mines, quarries, etc.
		without trees	619	Oil wasteland
	68	Rights-of-way	700	Large urban
	71	Urban forest land	730	Small urban
	72	Urban and other with trees	810	Interstate highway
			820	Paved federal or state highways
			830	Other paved roads
			840	Gravel road
			850	Dirt road
			860	Railroad
			870	Other (private) roads
Census water	90	Census water (> 660 ft wide or > 40 ac)	921-924	Census waterbody (> 40 ac)
			913	Perennial stream (>660 ft wide)
Non-census water	80	Non-census water (120-660 ft wide or 1-40 ac)	901	Waterbody (2-40 ac)
	89	Reserved non-census water (120-660 ft wide or 1-40 ac)	902	Waterbody (< 2 ac)
			911	Perennial stream (< 66 ft wide)
			912	Perennial stream (66-660 ft wide)

land definitions. FIA requires a minimum forest area width of 120 feet, while NRI requires a minimum width of only 100 feet. Both NRI and FIA require a minimum stocking of 10 percent, but interpretations differ. The 10-percent stocking requirement is generally adhered to by FIA, but it has been modified to include several western woodland types where stocking cannot be determined, and the condition has (or has had in the past) at least 5 percent canopy cover by trees of any size. In the Oregon project, FIA used an operational definition for designating an area of 10-percent stocked forest as having a 10-percent cover (Goebel and others 1998). The NRI interprets 10 percent stocked, when viewed from a vertical direction, as a canopy cover of 25 percent or greater. The FIA interprets 10 percent stocked, in terms of basal area per acre and/or number of trees per acre, as a comparison of the degree of occupancy of land by live trees compared to the growth potential of the land. FIA has a wide range of forest subcategories, while NRI has two: grazed and not grazed.

Within the forest land category, we also compared area estimates of forest type. The NRI and FIA both use forest type categories defined by the Society of American Foresters (SAF). The 1997 NRI database includes forest cover type data that we compared with those in the FIA inventories. Because FIA does not recognize the oak-pine forest type in Minnesota, the NRI data in the oak-pine forest type (representing approximately 80.3 thousand acres) were reassigned to the red-white-jack pine forest type.

The second land cover/use category, cropland/pastureland, includes a wide range of NRI land cover/use categories and a more limited group from FIA. This cropland/pastureland category includes orchards and other horticultural crops, cultivated cropland, noncultivated cropland, pastureland, and Conservation Reserve Program (CRP) land. The third land cover/use category, other rural land, includes farmsteads, Christmas tree plantations, wooded strips and windbreaks not large enough to meet the forest definition, barren land, and marshland. Developed land is the fourth land cover/use category. The NRI includes forested land less than 10 acres in size within urban and built-up areas as urban. Although normally considered forest land, the FIA urban forest land use code (71) is included in the developed land category so that this grouping would include areas of similar land types. The NRI categories for mines, quarries, gravel pits, and borrow pits (613) and for oil wasteland (619) are included with developed land since these would be categorized by FIA as urban and other (67, 72). Although

the NRI estimates that approximately 180,000 acres of Minnesota are in the first category (613), none are in the oil wasteland category. Both FIA and NRI use the U.S. Bureau of Census definitions for large (census) water, the fifth land cover/use category. Note that Census water is not included in Federal land ownership. In both inventories, the small (non-census) water category—the sixth land cover/use category—includes smaller streams and bodies of water.

The land cover/use categories for this study were compared on non-Federal land. No land cover/use data were collected for NRI points that fell on federally owned land. FIA plots that are field-visited have an ownership category recorded from which Federal ownership can be determined. A land cover/use, but not ownership, is recorded for non-forested FIA plots that are not field-visited. Because of these inventory differences, we determined that 1) land cover/use comparisons for FIA and NRI data must be made within the non-Federal land ownership, and 2) FIA data must first be separated into Federal and non-Federal groupings. For FIA plots having a recorded ownership class, the FIA ownership was used. For FIA plots with no recorded ownership, the geostatistical estimation data for the 1997 NRI (Nusser and others 1999) provided the GIS layer used in this study to determine if the FIA plots were located on Federal or non-Federal land.

FEDERAL GIS LAYER

The geostatistical estimation data for the 1997 NRI were used as a GIS layer in this study to assign Federal and non-Federal ownership to FIA plots with no recorded ownership. The NRI constructed this data set to provide geostatistical information on total surface area, surface area of Federal land, and area in large water bodies and large streams for each sub-county area, referred to as a HUCCO. The area intersected by the boundaries of a county and four-digit hydrologic unit area (see <http://www.nhq.nrcs.usda.gov/land/meta/m2143.html>) forms a HUCCO. The NRI uses this data set in the estimation process to develop area expansion factors for its point data.

To construct the geostatistical data layer, Census TIGER digital line files from 1995 were obtained from the U.S. Bureau of the Census (see www.census.gov/ftp/pub/geo/www/tiger/). These files represent 1:100,000 scale maps that delineate county boundaries, water bodies and streams, roads, and other land features. The 1998 release of a digital layer for Federal lands, updated to 1996 conditions and at a scale of 1:2,000,000, was obtained from the U.S. Geological Survey (USGS). When

TIGER information on Federal land was consistent with the USGS data, Federal boundaries were extracted from the TIGER data. Otherwise, Federal boundaries were extracted from the USGS layer. The National Oceanic and Atmospheric Administration (NOAA) shoreline was modified to exclude water areas extending beyond the shoreline of the U.S. coast for counties bordering the oceans and Great Lakes and to include islands belonging to the coastal counties. The shoreline modification was used to match NRI land definitions and is often referred to as the Lawson shoreline (Nusser and others 1999).

DATA

FIA data from the 1977 and 1990 periodic inventories and the 1999 annual inventory were used in the analysis. The periodic FIA inventories were historically conducted on a State-by-State basis at approximate intervals ranging from 6 to 8 years in the South and 11 to 18 years elsewhere (Gillespie 1999). The Agricultural Research, Extension, and Education Reform Act of 1998 directed the FIA program to conduct an annual inventory; FIA has begun to implement that inventory at an approximate rate of 20 percent per year in the East. The 1999 FIA data are taken from the first year of annual data collected in Minnesota and have subsequently fewer observations (1,821 plots) than the 1977 and 1990 data with 35,964 and 43,955 plots, respectively (McRoberts 1999, Brand and others 2000). Note that the 1977 and 1990 FIA inventories in Minnesota contained three times the number of plots in the base program (referred to as triple intensity), while the 1999 inventory contains 20 percent of the plots in the base program.

This study includes 1997 NRI data for the years 1982, 1987, 1992, and 1997, with 24,426 observations. The NRI has also begun a continuous inventory (with partial implementation in 2000 and full implementation in 2001) in which observations on 20 to 25 percent of the sampling units will be collected annually on sets of core and rotational sampling units. Neither the NRI continuous inventory data nor the FIA annual inventory data from 2000 and 2001 were available for inclusion in this paper.

DESIGN AND ESTIMATION

The sampling design for FIA is double sampling for stratification, conducted in two phases (Hansen and others

1992; Schreuder and others 1993 on page 188; http://www.srsfia1.fia.srs.fs.fed.us/statistics_band/stat_documents.htm). All FIA estimates and sampling errors provided here are based on stratified random sampling estimators with stratification after the selection of the sample (poststratification) presented in Cochran (1977 on pages 134-135) with finite population correction ignored. The sampling design of the NRI surveys is a stratified two-stage area sample (Nusser and Goebel 1997, Goebel 1998, Nusser and others 1998, Fuller 1999, Fuller and others 2001). The NRI area estimates and standard errors are obtained with stratified cluster sampling estimation techniques based on Cochran (1977 on pages 288-289).

RESULTS

Estimates of totals and standard errors for areas of non-Federal land in each of the land cover/use categories in table 1 were made for the NRI and FIA data using the statistical estimation procedures specified in the prior section. The results are given for the NRI and FIA data in tables 2 and 3, respectively. The NRI uses the U.S. Bureau of Census data for State total area, Federal land, and Census water as control data in the assignments of weights and therefore no standard errors are included for these categories. Similarly, no standard errors are reported for Census water and total area in table 3 of FIA estimates. The total area for Minnesota in tables 2 and 3 differs slightly. The FIA uses the 1970, 1980, and 1990 U.S. Census data values for their 1977, 1990, and 1999 inventories, respectively. The NRI database updates total land area for past inventories to that of the current inventory so that trends over time may be compared. Therefore, NRI totals for the years 1982-1997 in the 1997 database are based on the 1990 U.S. Census figures. The NRI definition for land included in shoreline, as mentioned in the section entitled Federal GIS Layer, causes slight deviation from the U.S. Census figure. Area estimates of non-Federal forest land by forest type categories are given in table 4.

Although the inventories are conducted at different dates, the NRI estimates of area in non-Federal forest land in Minnesota are all greater than those of FIA by nearly 2 million acres (tables 2 and 3). The NRI estimates of non-Federal forest area over the years from 1982 to 1997 show an increase of between 133.2 and 403.2 thousand acres (based on 95 percent confidence intervals for change), with an increase of between 170.9 and 359.1 thousand acres between 1992 and 1997.

Table 2.—NRI area estimates for land cover/use categories in Minnesota. Standard errors for estimates are in parentheses.

	1982 NRI		1987 NRI		1992 NRI		1997 NRI		1982-1997 change	
	-	-	-	-	-	-	-	-	-	-
	Thousand acres									
Nonfederal	47,953.5		47,932.1		47,936.2		47,936.3			
Forest land	15,980.1	(230.6)	15,903.2	(232.8)	15,983.3	(233.3)	16,248.3	(231.3)	268.2	(68.9)
Crop/pastureland	26,897.3	(243.6)	26,780.7	(235.3)	26,579.8	(232.9)	26,392.0	(234.1)	-505.3	(69.7)
Other rural land	2,780.6	(106.9)	2,822.6	(109.6)	2,842.7	(111.2)	2,536.4	(103.5)	-244.2	(44.0)
Developed land	1,901.0	(60.9)	2,028.7	(62.4)	2,131.4	(64.2)	2,365.1	(69.0)	464.1	(37.7)
Non-census water	394.9	(16.8)	396.8	(16.9)	399.1	(17.2)	394.5	(17.1)	-0.4	(7.5)
Federal land	3,326.3		3,342.3		3,336.3		3,336.3			
Census water	2,729.7		2,735.6		2,737.3		2,737.3			
Total	54,009.9		54,009.9		54,009.9		54,009.9			

Because the NRI sampling locations do not change between inventories, the NRI is a trending database and paired comparisons make it possible to place standard errors on the estimates of change. The FIA inventories indicate a slight decline in non-Federal forest land between 1977 and 1990 by approximately 0.3 million acres, but an overlap of the 95 percent confidence intervals for the estimates from the 1990 and 1999 inventories indicate there is no difference in estimates of non-Federal forest land. The NRI estimates a loss of between 368.7 and 641.9 thousand acres of non-Federal cropland/pastureland in Minnesota between 1982 and 1997, with between 201.7 and 433.3 thousand acres of that loss occurring between 1982 and 1992. The 1977 and 1990 FIA estimates of the area of non-Federal land in the cropland/pastureland show an approximate 476-thousand acre decrease. The FIA area estimates for non-Federal land in the other rural

land and developed land categories are higher than to those of NRI. Both the NRI and FIA area estimates of developed land increase over time.

DISCUSSION

Differences in definitions for land cover/use categories by the NRI and FIA may contribute to differences in estimates of area for the six categories of non-Federal land. Area estimates of non-Federal forest land by the NRI are greater than those of FIA. Both the FIA and NRI use forest land definitions of 10 percent stocking and a minimum size of 1 acre. However, the FIA requires strips of forest land to be at least 120 feet in width, while the NRI requires only a 100-foot width. A 10-percent stocking level is interpreted by the NRI as 25 percent

Table 3.—FIA area estimates for land cover/use categories in Minnesota. Standard errors for estimates are in parentheses.

	1977 FIA		1990 FIA		1999 FIA	
	-	-	-	-	-	-
	Thousand acres					
Nonfederal	47,766.9		47,392.4		47,638.5	
Forest land	14,102.5	(54.2)	13,843.7	(51.4)	13,556.8	(294.5)
Cropland/pastureland	27,307.7	(75.4)	26,831.7	(71.6)	27,122.5	(416.6)
Other rural land	3,775.1	(28.0)	3,958.7	(27.5)	3,681.3	(153.5)
Developed land	2,343.9	(22.1)	2,450.9	(21.6)	2,886.7	(135.9)
Non-census water	237.7	(7.0)	307.4	(7.7)	391.2	(50.0)
Federal land	3,212.7	(25.9)	3,516.5	(25.9)	3,286.7	(145.0)
Census water	3,058.7		3,107.1		3,107.1	
Total	54,038.3		54,016.0		54,032.2	

cover, as viewed from above. This interpretation may include areas of forest land that have less than 10 percent stocking. Table 4 provides a breakdown of estimated non-Federal forest land area into forest types. The estimated acres of non-stocked forest land by the NRI are much lower than those of the 1990 and 1999 FIA. Although the inventories were conducted for different years, the NRI area estimates for the red-white-jack pine forest type are nearly double those of the FIA, while the FIA area estimates of maple-beech-birch and non-stocked are more than twice those of NRI.

Data collection procedures may also contribute to the differences in estimates. In 1982, all NRI points were field-visited with aerial photograph (scale 1:7900) in hand. In the 1992 NRI, about 25 percent nationally were field-checked, while in 1997 a smaller percentage were field-checked. All 1977 Minnesota FIA Phase 2 plots that were forested or possibly forested, based on Phase 1 stratification, were field-visited. For the 1990 Minnesota FIA inventory, aerial photos (1:15,840) of all 1977 ground plots were examined (Miles and others 1995). The photos were used to classify the 1977 ground plots as either disturbed or undisturbed forested plots and for part of the State, verification of the photointerpretation for undisturbed forest plots was done

from fixed wing aircraft. All disturbed forest plots and one-third of undisturbed forest plots were field-visited, and models were used to update the remaining undisturbed forest plots. A smaller percentage of non-forested FIA Phase 2 plots were field-visited and remote sensing (e.g., aerial photos) was instead used to assign the plots to land use categories.

CONCLUSIONS

The sampling methods and definitions used by the FIA and NRI inventory programs may contribute to differences in area estimates for the various land cover/use categories outlined in this paper. Both agencies use definitions that rely on a combination of land cover and land use. While land cover classifications are based strictly on the current cover observed on the land, land use is more convoluted. Classifications based on land use are interpretations of how the land is used. The forest land definition, for example, includes land that is forested now or has been forested in the past but that has not been converted to any other use. With the expanding use of remote sensing by both agencies, common definitions based on land cover would provide a venue for closer agreement of area estimates in those classes. Continuing with the forest land

Table 4.—Area estimates of non-Federal forest land in Minnesota by forest type. Standard errors for estimates are in parentheses.

	1977 FIA		1990 FIA		1997 NRI		1999 FIA	
	(Thousand acres)		(Thousand acres)		(Thousand acres)		(Thousand acres)	
White-red-jack pine	584.2	(11.0)	696.3	(11.5)	1,273.2	(137.0)	620.2	(63.0)
Spruce-fir	2,447.2	(22.6)	3,443.4	(25.6)	3,897.4	(182.9)	2,546.5	(127.7)
Oak-hickory	922.2	(13.9)	1,160.1	(14.9)	1,765.4	(85.7)	1,460.7	(96.7)
Elm-ash-cottonwood	922.3	(13.9)	1,291.9	(15.7)	1,923.4	(112.3)	1,355.5	(93.1)
Maple-beech-birch	1,063.4	(14.9)	1,303.9	(15.8)	593.4	(56.2)	1,214.7	(88.2)
Aspen-birch	5,766.2	(34.7)	5,572.0	(32.6)	6,672.6	(247.6)	5,813.5	(192.9)
Non-stocked	2,105.2 ^a	(20.9)	376.1	(8.5)	122.9	(29.5)	270.7	(41.6)
Total	13,810.7	(53.6)	13,843.7	(51.4)	16,248.3	(231.3)	13,281.7	(291.5)

^a Note that the 1977 FIA estimate for area of nonstocked forest land is based on a definition of nonstocked forest land that caused many more plots to be classified as nonstocked in 1977 than the definition that is currently used by FIA. In 1977 a plot was classified as nonstocked if it did not have sufficient stocking in live growing-stock trees (trees of commercial species that have or potentially have a merchantable saw log in them). The new definition of nonstocked excludes only dead trees; it does not exclude noncommercial species or cull trees that do not contain a saw log or potential saw log.

example, forest land that is clearcut may initially be assigned to a land cover class of grass, followed by shrubland as regeneration occurs, and finally forest land as the trees mature. The land use definitions may be retained as additional types of classifications by each of the agencies to meet their needs, while the land cover definitions would provide the common classifications.

A common digital base map with Federal boundaries and Census water superimposed on other political boundaries could provide a common county-level data set for use by both agencies. The geospatial GIS layer, constructed for use by the NRI and used in this study, may be the first iteration of this type of data layer.

Further work needs to include investigation into why the FIA and NRI estimates are seemingly different. It may be an issue of ownership; misclassification of plots as Federal or non-Federal may have led to differences. Closer inspection of differences should be investigated geospatially, by land cover/ use category, and other factors to better understand where the differences lie and how to reconcile those differences.

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A STATISTICALLY VALID METHOD FOR USING FIA PLOTS TO GUIDE SPECTRAL CLASS REJECTION IN PRODUCING STRATIFICATION MAPS

Michael L. Hoppus and Andrew J. Lister ¹

ABSTRACT.—A Landsat TM classification method (iterative guided spectral class rejection) produced a forest cover map of southern West Virginia that provided the stratification layer for producing estimates of timberland area from Forest Service FIA ground plots using a stratified sampling technique. These same high quality and expensive FIA ground plots provided ground reference data for the classification method. Dividing the counties in the southern portion of the state into two groups, and using the FIA plots in each county group to make the strata for the other, avoids the potential bias incurred by having the plots stratify themselves. This procedure achieved the required precision of 3 percent sampling error per million acres of timberland.

BACKGROUND

The Forest Inventory and Analysis (FIA) program of the USDA Forest Service is responsible for inventory and monitoring of the Nation's forests. Congress mandates, through the Forest and Rangeland Renewable Resources Planning Act of 1974 and the McSweeney-McNary Forest Research Act of 1928, that FIA continuously determine the extent, condition, volume of timber, growth, and depletion of the Nation's forest land. In the East, statistical estimates derived from FIA inventories must meet specified sampling errors; for example, a 3-percent error per 1 million acres of timberland is the maximum allowable sampling error for area. Timberland is defined by FIA as forest land that is producing or capable of producing crops of 20 cubic feet of industrial wood per acre per year (Hansen and others 1992). Until now, FIA has reached this precision in part by stratifying the FIA ground plots using aerial photos and implementing a stratified sampling technique (Cochran 1977). However, the Agricultural Research, Extension, and Education Reform Act of 1998 (PL 105-185) directs all FIA units to change from an inventory frequency of 10 to 14

years per state to an annual inventory system that ground samples 20 percent of each state per year (Gillespie 1999). This new inventory design requires plot stratification every 5 years.

The Northeastern FIA unit, responsible for surveying 13 Northeastern States, uses aerial photos from the National Aerial Photography Program (NAPP) for FIA ground plot stratification. NAPP currently is on a 7-year cycle. The high cost of additional qualified photointerpreters necessary to complete aerial photo stratification in all the states on a 5-year cycle plus the 7-year cycle of NAPP has led to investigations of the use of satellite imagery to create a stratification layer for stratifying the ground plots into homogeneous groups in order to reduce the variance of estimates (Cochran 1977). Furthermore, satellite image classification provides a forest cover map that can be used to evaluate forest distribution and change over space and time.

OBJECTIVES

The primary purpose of this project was to estimate the timberland area contained within the 14 southern counties of West Virginia. Additionally, we wanted to make and evaluate FIA's first practical application of satellite image-based stratification. Preliminary results of this analysis were requested by the State forester of West Virginia. An

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important goal of the image classification design was to use the FIA ground plots as reference data in a statistically valid way. The plots provide abundant high quality ground truth that is well distributed, recent, and accurately located with GPS. The risk, of course, is that use of the plots to make stratification maps may produce statistically invalid estimates from a post-stratified random sampling method, i.e., the plots might erroneously be used to derive the stratification layer that will then in turn be used to stratify them. We hypothesized that timberland area estimates produced from stratification of the plots based on satellite imagery would be more precise than estimates provided by simple random sampling of ground plots.

METHODS

Ground Plots

FIA ground plots were distributed randomly over the landscape in the 14 counties of the FIA's Southern unit of West Virginia with an intensity of approximately one plot per 6,000 acres or one plot about every 3 miles. Data were collected in 2000 and 2001. Many data were obtained on each plot in accordance with FIA protocol, including current land use class. Timberland is one land use class whose area can be estimated from the survey (USDA Forest Service 2001).

The layout and geometry of the ground plots have implications for use as image classification reference data. Two issues must be considered when comparing the pixel brightness values of Landsat TM images and their corresponding FIA plot data. First, the FIA plot consists of four 48-foot-diameter circular subplots: one in the center, and three symmetrically separated from the central subplot by 120 feet (fig. 1). This means that the plot places a subplot on a minimum of 4 pixels. Each subplot covers only 19 percent of the area of a pixel. Second, the location accuracy of the pixel is plus-or-minus 30 m on average and the GPS location accuracy of the plot center is about plus-or-minus 10 m. Therefore, there is not a clear one-to-one relationship between plot data and a single pixel. We have found from previous work that plots closer than about 90 m (3 pixel widths) to a different land cover type should not be used for reference data to classify pixels. For the same reason, only plots that have a single land use class over the four subplots should be used to help classify the satellite image.

The plot coordinates were converted to a vector GIS representation of the information. ERDAS Imagine (ERDAS, Atlanta, Georgia 30329) image processing software was used for image classification.

Satellite Image Classification

An innovative classification technique called Iterative Guided Spectral Class Rejection (IGSCR) was used to produce a forest/nonforest map of the area from the six non-thermal bands of Landsat TM. This technique was developed with the specific objective of producing FIA phase 1 inventory: FIA plot stratification to improve the precision of estimates (Wayman and others 2001). At its core, the method uses a large number of reference pixels, whose spectral signatures and forest or nonforest information class are known, to label the spectral classes created from an unsupervised classification. An unsupervised classification is a common technique used to group pixels that have similar spectral characteristics. Acquiring sufficient amounts of accurate forest reference data that can be used for creating the pool of reference pixels is often very difficult and expensive (Congalton and Biging 1992). This project made use of the large number of existing FIA ground plots as its source of high quality, accurately located reference data to be used as training sites for image classification.

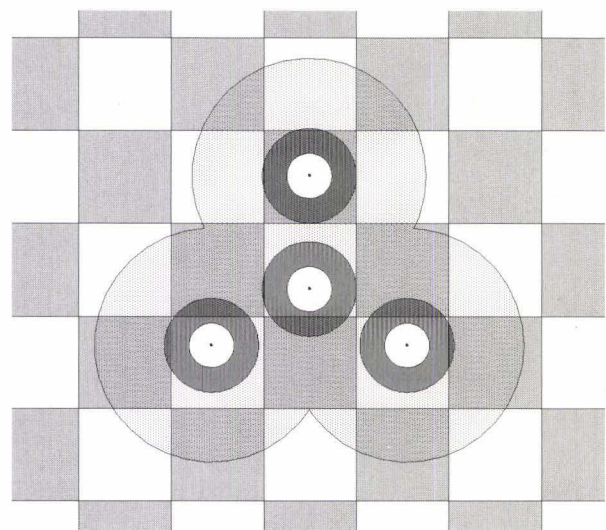


Figure 1.—The FIA ground plot geometry versus 30-m TM pixels. The plot consists of a cluster of four 0.017-ha subplots. The dark gray circles represent the area of locational error due to GPS errors. The larger gray circles represent the potential locational error due to image registration.

For details of the image classification algorithms and the ERDAS Imagine Software usage, see ERDAS (1997). Reference pixels for forested areas were identified by overlaying the location of homogeneous timberland plots onto the satellite image using ERDAS Imagine. By using a region growing tool in this software, a cluster of spectrally similar pixels was created for each timberland plot. Reference pixels for nonforest areas were created by interpreting digital ortho-maps and growing a region of spectrally similar pixels at the corresponding location on the satellite imagery. We did not use nonforest FIA plots for locating nonforest training sites because FIA plots do not characterize nonforest areas well from a spectral point of view. Areas covered with trees may have a nonforest definition, such as city parks. Typical nonforest areas, such as roads, buildings, quarries and pastures, are easy to identify on digital ortho-maps.

Four raw Landsat TM images that cover the area were mosaicked together. Documentation on how the software performs this task is weak, and there was some concern that differences in pixel brightness values between scenes at the overlap area would create spectral confusion. A careful examination of the finished forest/nonforest map showed no evidence of mapping inaccuracies along the seams of the mosaicked images. However, it is important to note that when maps were produced from the same mosaic, using more traditional supervised and unsupervised classification methods, definite inconsistencies occurred at the seams. The classification method we used did not appear to produce any noticeable inconsistencies at the seam lines of the scenes. The satellite scenes were all acquired during late May and early June 2000.

An unsupervised classification (ISODATA) method clustered the mosaicked image into 100 spectrally similar classes. The IGSCR algorithm accepts and labels a spectral class when 90 percent of the reference pixels contained within a given class have the same information class: forest or nonforest. At least 10 reference pixels have to be located within the class. All classes not labeled in the first iteration are "rejected" into a single group of pixels that are again subjected to an unsupervised classification. A portion of these second iteration classes is labeled, and a third iteration of the process is performed. The signature files for all the classes labeled as pure forest or nonforest are then merged into one signature file and used in a supervised classification using the

maximum-likelihood decision rule. This resulted in a forest/nonforest raster map that was used as a basis for all stratification methods.

STRATIFICATION METHOD

A simple method was used to keep the plots from being stratified by the same map that they produced. The 14 counties were divided into two sets. FIA plots from each of the two county sets were used to create reference pixels that were used to produce two independent forest/nonforest maps using the IGSCR technique. The forest/nonforest maps of county set A were produced with the help of plots located only in county set B and vice versa. The result was that all FIA plots located in each of the counties were labeled, and their estimates weighted, by strata created from a map produced by plots located outside the county.

Stratified random sampling procedures were applied to the FIA plots located within the 14 counties of FIA unit 3 of West Virginia to estimate timberland area. For details of the stratified random sampling protocol, see Cochran (1977).

Three stratification designs were compared in this project:

1. Two strata—Forest and Nonforest;
2. Four strata—Forest, Nonforest, Forest within 2 pixels of Nonforest, and Nonforest within 2 pixels of Forest;
3. Four strata (based on the number of forested pixels within a 5 X 5 pixel window)—0-6 forested pixels, 7-17 forested pixels, 18-22 forested pixels, and 23-25 forested pixels.

A previous study found that nearly all of the significant Landsat TM predictor variables for timberland area on an FIA plot were based on images created by 3 X 3 or 5 X 5 filters. These filters were designed to calculate the average or standard deviation of pixel brightness values (raw bands and transformed layers) within the window or, when applied to classified images, they summed the count of forested pixels within the window (Hoppus and others 2001). This indicates that the geometry match between the plots and the TM pixels requires a measurement of each pixel's neighborhood for best results when using Landsat TM derived maps to stratify FIA ground plots. The numbers of forested pixels in each of the four strata based on the 5 X 5 pixel neighborhood were chosen based on the results of this study (fig. 2).

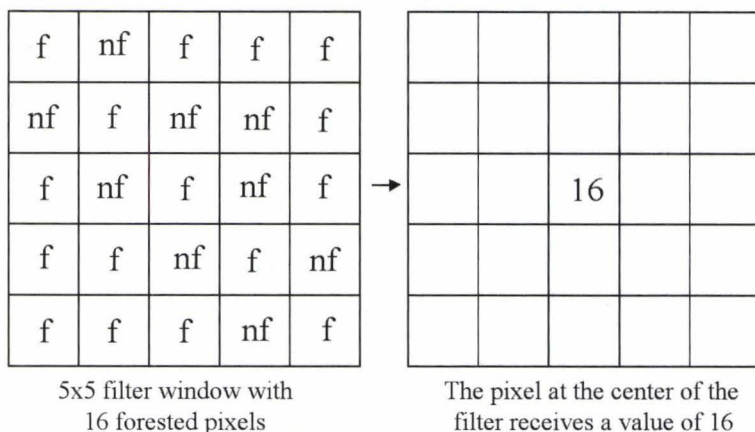


Figure 2.—Filtering the forest/nonforest map into strata. A 5 X 5 pixel filter window is passed over the forest/nonforest map. All forested pixels within the window are counted and the sum placed in the center of the window. This results in a new raster map of forest pixel counts. Pixels with values equal to forested neighborhood counts are grouped into strata.

Placement of an FIA plot into a given stratum was based on the value of the pixel coinciding with the center of the central subplot. It was predicted that the four strata designs would reduce the variance of the estimate of timberland area more than the two strata forest/nonforest design because they would be more likely to group plots based on their proximity to forest edges and/or areas of differing heterogeneity.

Stratified Estimation Formulae Using Satellite Derived Strata

The data collected were calculated using the FINSYS computer system developed at the Northeastern Research Station. The inventory estimates are based on stratified random sampling methodology.

Assumptions for the Image Strata:

1. Each image pixel in the entire strata is assigned to one of the classes, e.g., forest or nonforest.
2. Each plot is also assigned to one of the same set of classes.

Notation:

Each class is called a "strata" and for strata "h" (Cochran 1977)

N = total number of pixels

N_h = number of pixels in class h

n_h = number of plots in class h

$W_h = N_h / N$ proportion of total pixels in stratum "h"

y_{hi} = proportion of plot "i" in stratum "h" that is timberland

$\bar{y}_{hi}$ = mean proportion of timberland for stratum "h", which

$= \sum_{i=1}^{n_h} y_{hi} / n_h$ = estimate of the proportion of land area that is timberland for stratum "h"

L = total number of strata

1. To obtain an estimate of the proportion of timberland for the entire area, calculate a weighted mean of the individual stratum means. Weights should be proportional to the stratum size because it is improper to weight the mean representing a very small area the same as one representing a very large area. The overall stratified estimate is

$$\bar{y}_{st} = \sum_{h=1}^L W_h \bar{y}_h$$

2. The estimated variance of $\bar{y}_h$ is obtained with the sums of squares about the mean

$$s_h^2 = \sum_{i=1}^{n_h} (y_{hi} - \bar{y}_h)^2 / (n_h - 1)$$

and the variance of the mean is

$$\text{var}(\bar{y}_h) = s_h^2 / n_h$$

3. The estimated variance of $\bar{y}_{st}$, with a correction factor for a "finite population," is

$$\text{var}(\bar{y}_{st}) = \sum_{h=1}^L W_h^2 \text{var}(\bar{y}_h) (1 - f_h), \text{ where } f_h = n_h / N_h$$

4. To calculate an estimate of total timberland area, multiply the estimate of the mean proportion by the known total land area "A"

$$\hat{y}_{st} = A \times (\bar{y}_{st})$$

The variance of $\hat{y}_{st}$ is

$$\text{var}(\hat{y}_{st}) = A^2 \text{var}(\bar{y}_{st})$$

The standard error is the square root of $A^2 \text{var}(\bar{y}_{st})$

$$SE(\hat{y}_{st}) = A \times \text{var}(\bar{y}_{st})^{1/2}$$

5. The sampling error is equal to the standard error divided by the estimate

$$SE = A \times SE(\bar{y}_{st}) / \hat{y}_{st}$$

RESULTS

The estimates, sampling errors, and relative sampling efficiencies for total timberland in FIA unit 3 are presented in table 1. Simple random sampling of the plots, without stratification, provided an estimate of 4,005,380 acres of timberland with a sampling error of 1.6 percent. The required precision for this area is 1.5 percent in order not to exceed an FIA limit of 3 percent sampling error per million acres of timberland. All three of the stratification designs, based on forest/nonforest maps produced by applying the IGSCR technique to four mosaicked Landsat TM scenes, provided estimates with precisions less than 1.5 percent. It is clear that the stratification method that grouped and weighted the plots based on the number of forested pixels in the surrounding 25-pixel neighborhood reduced the variance of the estimate the most (table 1).

Another way to compare the efficiency of a stratification method is to calculate how many extra plots would be required to reduce the variance to the same level. The percent increase in precision is equal to

$$1 - (\text{original number of plots} / \text{original number plus extra plots})^{0.5}$$

A total of 1,722 plots are required to reduce the variance from 1.6 percent to 1.1 percent, the sampling error for the stratified sampling estimate provided by the 5 X 5 forested pixel sum. That's an increase of 908 plots at an additional cost of \$700,000.

DISCUSSION

Our results were consistent with those of McRoberts and others (in press), where forest land estimates of portions of four states were produced with more precision using a satellite-based stratification method with four strata with a 2-pixel edge. We had expected that stratified random sampling would lead to an increase in the precision of estimates of timberland area over those from simple random sampling. Our main concern, however, was that the satellite stratification technique would not reduce the variance below the acceptable limit. Furthermore, we wanted to devise a method that did not use the FIA plots to make a map that would be used to stratify the same plots. Our method of splitting the counties into two groups and using the opposite counties' plots for stratification does not violate the assumptions of independence of strata and the corresponding plots.

Table 1.—Estimates, sampling errors, and efficiencies for total timberland in FIA unit 3 of West Virginia provided by sampling FIA plots stratified three different ways using a forest/nonforest map. Four mosaicked Landsat TM scenes were classified using the IGSCR technique to produce the map

Landsat TM map strata	Timberland Acres	Sampling error Percent ^a	Efficiency Percent ^b
Simple Random Sampling	4,005,380	1.60 (3.20)	n/a
IGSCR (F/NF Plot-Pixel)	4,038,696	1.23 (2.47)	69
IGSCR (F/NF/2-Pixel Edge)	4,038,155	1.16 (2.33)	90
IGSCR (5X5 Pixel F Sum)	4,056,300	1.10 (2.22)	112

^a Sampling error for entire study area (per million acres of timberland).

^b Sample sizes would have to be increased by this percent to achieve the same precision without stratification.

Our results indicate that even without stratification, we would almost have met our requirements. It should be noted, however, that this region of West Virginia is approximately 80 percent forested. When sampling for proportions (forest and nonforest), the variance is generally greater when the two classes are nearly equal. In this study, the classes are not equal, and thus the variance is expected to be lower. Our results also indicate that stratification using the classification derived from the iterative guided spectral class rejection method detailed in Wayman and others (2001) can reduce variance below that from simple random sampling. We thus conclude that there is a clear benefit to using classified satellite imagery, not only from a variance reduction standpoint, but also for its possible use in other applications such as fragmentation analysis, change detection, and graphical display of forest land distribution.

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SYNERGISTIC USE OF FIA PLOT DATA AND LANDSAT 7 ETM+ IMAGES FOR LARGE AREA FOREST MAPPING

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ABSTRACT.—FIA plot data were used to assist in classifying forest land cover from Landsat imagery and relevant ancillary data in two regions of the U.S.: one around the Chesapeake Bay area and the other around Utah. The overall accuracies for the forest/nonforest classification were over 90 percent and about 80 percent, respectively, in the two regions. The accuracies for deciduous/evergreen/mixed and forest type group classifications were around 80 percent and 65 percent, respectively, and were consistent in the two regions. These results suggest that use of FIA plot data together with satellite imagery and relevant ancillary data may substantially improve the efficiency, accuracy, and consistency of large area forest land cover mapping.

Reliable and updated forest information is required for many scientific and land management applications. Meeting this requirement is of interest to both the Forest Inventory and Analysis (FIA) program of the USDA Forest Service and the Land Cover Characterization (LCC) Program of the U.S. Geological Survey (USGS) Earth Resources Observation Systems (EROS) Data Center (EDC). FIA has a mandate to collect and report information periodically on status and trends in the Nation's forested resources, while the LCC program has a mandate to develop a circa 2000 national land cover database through the Multi-Resolution Land

Characterization (MRLC) 2000 project. Therefore, it is in the best interest of the government that these two agencies collaborate in mapping the Nation's land cover. The current study is the result of an initial collaboration between the two agencies.

Forest land cover information is often derived from remotely sensed images using classification algorithms (e.g., Franklin and others 1986, Mickelson and others 1998), many of which require substantial amount of reference data (Hall and others 1995, Townshend 1992). Reliable reference data are also required for assessing classification results. One of the challenges to mapping forest land cover over large areas is the lack of adequate reference data. In areas where some reference data sets exist, they may have been collected in different ways and may have different levels of reliability. Such scarcity of reliable reference data and lack of consistency among the available data sets often limit the efficiency, consistency, and accuracy in deriving forest information from satellite imagery.

The plot data collected through FIA make up a potentially high quality reference data set for the MRLC 2000 project. FIA plots represent a statistically based sampling of the Nation's land. Detailed information on forest status and

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structure is collected periodically at each plot through intensive field work. With minimal efforts, this data set can be reorganized for use with remotely sensed images. The purpose of the current study is to evaluate the usefulness of the FIA plot data in deriving forest land cover classifications from satellite imagery over large areas and to test whether using this data set can improve the efficiency, accuracy, and consistency in developing the MRLC 2000 national land cover database.

DATA AND PREPROCESSING

Study Area

For mapping efficiency, the conterminous United States was divided into 66 mapping zones for the MRLC project. Two mapping zones—zones 16 and 60—were used in this pilot study (fig. 1). Zone 60 represents the eastern coastal environment, covering the Chesapeake Bay area, while zone 16 represents the western arid and less developed landscape, covering Utah and southern Idaho. Figure 1 shows the Landsat paths/rows covered by the two mapping zones.

type separability (Yang and others 2001a). These images were acquired between 1999 and 2001 and were selected to minimize the impact of cloud cover and atmospheric effects. The images were geometrically and radiometrically corrected using standard methods at the USGS EROS Data Center (Irish 2000). Terrain correction using the USGS 1-arc second National Elevation Dataset was performed to improve geolocation accuracy. Raw digital numbers were converted to at-satellite reflectance for the six reflective bands and to at-satellite temperature for the thermal band according to Markham and Barker (1986) and the Landsat 7 Science Data User's Handbook (Irish 2000). All seven bands were resampled to a 30-m spatial resolution. Tasseled-cap brightness, greenness, and wetness were calculated using at-satellite reflectance based coefficients (Huang and others 2002b).

Ancillary data included the USGS 1-arc second National Elevation Dataset and three derivatives: slope, aspect, and a topographic position index. In addition, three soil attributes—available water capacity, soil carbon content and a soil quality index—were derived from the State Soil Geographic (STATSGO) Data Base. All ancillary data layers were resampled to a spatial resolution of 30 m.

Landsat Imagery and Ancillary Data

For each Landsat path/row covered by the two mapping zones, Enhanced Thematic Mapper Plus (ETM+) images were acquired on three different dates to capture vegetation dynamics over a growing season and to maximize land cover

Reference Data Sets

Through intensive field work, the FIA program provides detailed forest attributes at individual tree, subplot, and plot levels. Considering the pixel size of the ETM+ imagery and

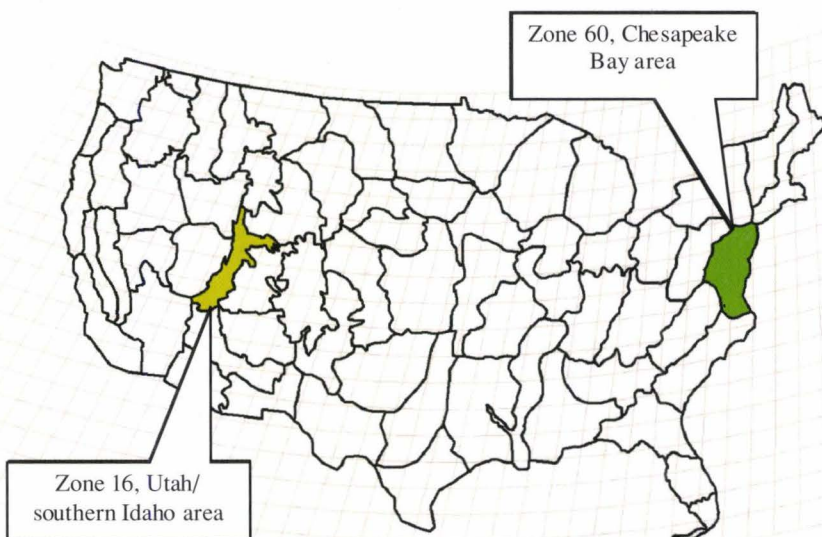


Figure 1.— Mapping zones of the conterminous U.S., with the two study areas shaded. The background grid represents Landsat 7 path/row boundary.

Zone 60, Chesapeake Bay area

Zone 16, Utah/ southern Idaho area

possible geolocation errors of the imagery and FIA plots, only plot-level data were deemed appropriate for use with the ETM+ imagery. Therefore, tree-level data were summarized to subplot level and then to plot level. In zone 60, each plot was labeled with single- or multiple-condition primarily depending on if there were only one or multiple land use/land cover types within the plot area. Multiple-condition plots were excluded to minimize the impact of misregistration errors and other possible inconsistencies between FIA plots and the satellite images. This was not deemed necessary in zone 16 because most of the plots were based on the plot design used prior to 1995, which restricts all plots to single-condition. Each eligible plot was then classified at three levels: forest/nonforest, deciduous/evergreen/mixed, and forest type group. Table 1 lists the number of FIA plots used in this study. Global Positioning System units were used to locate all plots in zone 60 and 147 plots in zone 16. The remaining plots in zone 16 were digitized from aerial photos used in the field. Geolocation errors between the digitized plots and ETM+ images were minimal. A visual check of over 100 random plots digitized from the air photos against corresponding satellite images suggested that less than 10 percent of the plots had location errors greater than one ETM+ pixel.

Table 1.—Number of FIA plots used in this study

	Zone 60	Zone 16
Forest/nonforest	1,750	3,037
Deciduous/evergreen/mixed	669	1,754
Forest type group	669	1,852

Another reference data set available in zone 16 consisted of field data collected by the Fire Science Lab of the Rocky Mountain Research Station of the USDA Forest Service and the Utah GAP Analysis Program of Utah State University. Each field site was classified at two levels: forest/nonforest and deciduous/evergreen/mixed. This was used as an independent data set to evaluate the classification results developed using FIA plot data in mapping zone 16. Although the point location was not based on any statistically rigorous sampling design and the evaluation should not be considered a statistically rigorous accuracy assessment, this independent reference data set should provide useful information on the consistency of FIA plot data and the reliability of derived classifications.

METHODS

Classification Levels

As with the reference data, classification of the ETM+ images and ancillary data was performed at three levels: forest/nonforest, deciduous/evergreen/mixed, and forest type group. A forest/nonforest map is required by FIA to implement a stratified sampling of forested land in order to produce accurate estimates of forest attributes. Deciduous, evergreen, and mixed are the main forest categories in the MRLC 2000 classification scheme. Type group information is often required for species conservation planning, fire management, and many other applications. Table 2 lists the major forest type groups in the two mapping zones.

Table 2.—Forest type groups in the two mapping zones

Zone 60	Zone 16
Spruce/fir	Pinyon/juniper
Loblolly & shortleaf pine	Douglas-fir
Oak/pine	Ponderosa pine
Oak/hickory	Fir/spruce/mountain hemlock
Oak/gum/cypress	Lodgepole pine
Elm/ash/red maple	Other western softwoods
	Aspen/birch
	Western oak
	Other western hardwoods

Decision Tree Classifier

Many algorithms are available for classifying satellite images (Hall and others 1995, Townshend 1992); among the most popular of these include the maximum likelihood classifier, neural network classifiers, and decision tree classifiers. Decision tree was chosen for this study because it 1) is non-parametric and therefore independent of the distribution of class signature, 2) can handle both continuous and nominal variables, 3) generates interpretable classification rules, and 4) is fast to train and is often as accurate as, and sometimes more accurate than, many other classifiers (Hansen and others 1996, Huang and others 2002a). The decision tree program used in this study, C5, employs an information gain ratio criterion in tree development and pruning (Quinlan 1993). This program has many advanced features, including boosting and cross-validation.

Boosting

Boosting is a technique for improving classification accuracy (Bauer and Kohavi 1998). With this function, the program develops a sequence of decision trees, each subsequent one trying to fix the misclassification errors in the previous tree. Each decision tree makes a prediction. The final prediction is a weighted vote of the predictions of all trees. This function often improves classification accuracy by 5 to 10 percent (e.g., Friedl and others 1999).

Cross-Validation

Cross-validation is designed to obtain relatively realistic accuracy estimates using a limited number of reference data samples for both training and accuracy assessment (Michie and others 1994). For an *N*-fold cross-validation the training data set is divided into *N* subsets. Accuracy estimates are derived by using each subset to evaluate the classification developed using the remaining training samples, and their average value represents the accuracy of the classification developed using all reference samples.

RESULTS AND DISCUSSION

Classification accuracies at all three levels in the two mapping zones were estimated through cross-validation (table 3).

These accuracy estimates can be considered reasonably realistic, because the FIA plots are not spatially auto-correlated, they cover the entire of each study area, and their locations were determined through statistically based sampling designs (Michie and others 1994). This point is demonstrated by the fact that for the forest/nonforest and deciduous/evergreen/mixed classifications in zone 16, the accuracies estimated using the independent reference data set collected by the Fire Science Lab of the Rocky Mountain Research Station and the Utah GAP Analysis Program were similar to those estimated through cross-validation (table 3).

With the boosting function of the C5 program, overall accuracies of around 80 to 90 percent, 80 percent, and 65 percent were achieved in both mapping zones for the forest/nonforest, deciduous/evergreen/mixed, and forest type group classifications, respectively. At the three classification levels, the boosting function improved classification accuracy by about 2 to 10 percent in absolute values. Similar improvements using the boosting function have been reported in other studies (e.g., Chan and others 2001). The final classifications in the two study areas were developed using the boosting function. The classifications in zone 16 were evaluated by field crews of the Rocky Mountain Research Station and the Utah GAP Analysis Program. Both parties agreed that these classifications were reasonably accurate.

Despite the very different landscapes, classification accuracies for the two mapping zones are comparable at the deciduous/evergreen/mixed level and at the forest type group

Table 3.—Classification accuracy estimates for the two mapping zones

Classification level	Forest/nonforest		Deciduous/evergreen/mixed		Forest type group	
	Accuracy	Std. error	Accuracy	Std. error	Accuracy	Std. error
- - - - -Percent- - - - -						
Zone 60, cross-validation						
Without boosting	90.7	0.4	74.0	1.4	59.6	1.1
With boosting	93.7	0.7	78.9	0.8	66.1	2.2
Zone 16, cross-validation						
Without boosting	80.4	0.4	78.0	0.4	56.6	0.9
With boosting	82.7	0.4	81.2	0.6	65.8	1.2
Zone 16, use of independent test data set						
Without boosting	75.7	-	75.3	-	-	-
With boosting	79.0	-	83.4	-	-	-

level, suggesting that similar accuracies are likely achievable in other areas using FIA plot data, Landsat 7 imagery, and relevant ancillary data.

However, the forest/nonforest classification in zone 16 is about 10 percent less accurate than in zone 60. This is probably because some forest and natural nonforest vegetation are more difficult to separate both spectrally and physiologically in the arid environment of zone 16. Even from the ground, some field crews recognized that it is sometimes very difficult to separate tall shrubs from sparse short trees without ambiguity. Considering the complex topography and the difficulty in defining forests in zone 16, the accuracies achieved in this zone probably represent the lower end of the accuracies expected in forest/nonforest classifications throughout the Nation.

The development of the classifications in each mapping zone took an experienced person about 3 to 4 months, including pre-processing of the ETM+ images and ancillary data discussed earlier. Our experience from developing the 1992 National Land Cover Dataset (Vogelmann and others 2001) suggests that if the FIA plot data had not been readily available for this study, at least one-third extra time and effort would have had to be devoted to reference data collection. For the MRLC 2000 project, even if some resources are available for reference data collection, the spatial coverage and location of collected reference data points very likely will not be as preferable as the FIA plot data.

The ability of the cross-validation to produce accuracy estimates at the classification stage can be highly valuable to many users of regional classifications, because statistically rigorous accuracy assessment of such classifications can be very expensive and often takes a long time before any accuracy estimate can be derived (Yang and others 2001b, Zhu and others 2000). In order for the cross-validation estimates to be as little biased as possible, however, the reference data should not be spatially auto-correlated and should be collected through a statistically based sampling design (Friedl and others 1999, Michie and others 1994). The FIA plot data make up perhaps one of the few readily available reference data sets for regional applications that meet these criteria.

CONCLUSIONS

1. FIA plot data are useful reference data for mapping forest land cover at regional and national scales. Forest maps developed using this data set, Landsat 7 ETM+ image, and ancillary data in the two mapping zones had overall accuracies of about 80 to 90 percent, 80 percent, and 65 percent at the forest/nonforest, deciduous/evergreen/mixed, and forest type group levels, respectively.
2. Use of FIA plot data as part of the reference data set in the MRLC 2000 project can substantially improve mapping efficiency, accuracy, and consistency. The spatial coverage of the plots and the statistically based sampling design of plot location make it possible to produce reasonably realistic accuracy estimates at the classification stage.
3. The decision tree classifier proves a viable and efficient method for deriving forest classifications over large areas. The boosting function can improve classification accuracy by 2 to 10 percent in absolute value.
4. Synergistic use of FIA plot data and satellite imagery at a national scale likely will benefit both USGS EDC's MRLC 2000 program and the FIA program of the USDA Forest Service.

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A 30-METER SPATIAL DATABASE FOR THE NATION'S FORESTS

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ABSTRACT.—The FIA vision for remote sensing originated in 1992 with the Blue Ribbon Panel on FIA, and it has since evolved into an ambitious performance target for 2003. FIA is joining a consortium of Federal agencies to map the Nation's land cover. FIA field data will help produce a seamless, standardized, national geospatial database for forests at the scale of 30-m Landsat pixels. This database includes classifications of forest types, estimates of percent tree cover, and other land attributes that can be used in geospatial models for large-area assessments. Mapping of more detailed forest conditions is feasible.

EVOLUTION OF A VISION

Today's vision for operational remote sensing in the Forest Inventory and Analysis² (FIA) Program began 10 years ago with the First Blue Ribbon Panel³ on FIA (AFPA 1992). The panel included national leaders from all sectors of the forestry community. In its report, the panel recommended that FIA implement satellite remote sensing to improve cost-effectiveness and that FIA should have a "preeminent position in all federal efforts to inventory and monitor forest resource conditions at the regional and national levels."

In 1997, the Office of Science and Technology Policy⁴ developed a framework for the Nation's environmental inventory and monitoring programs, including FIA (CENR 1997). In its report, the office noted that existing programs are based on conflicting definitions and methods that constrain the availability and affordability of geospatial data for the Nation. Rather, these programs need to "be conducted in a coordinated fashion and provide the types of integration that have so far been unachieved."

The following year, the FIA Blue Ribbon Panel⁵ issued its second report (AFPA 1998). The panel recommended that FIA produce more timely and consistent information by converting to an annual forest inventory system, which would require development of new and expanded remote sensing technologies. In its report, the panel recommended that FIA should prepare a vision for operational remote sensing, create an extensive Web site containing forest maps produced by FIA, use remote sensing to improve areal estimates of forest cover for small geographic areas, and collaborate with other agencies in remote sensing endeavors. The report includes an unusually strong criticism: "FIA has been unable, for a variety of reasons, to demonstrate the leadership that was called for by the first Blue Ribbon Panel: 'FIA should also have a preeminent position in all federal efforts to inventory and monitor forest resource conditions at the regional and national levels.'" The panel asked FIA to develop a set of performance-based measures⁶ with timetables and periodic assessments to evaluate achievement.

Later that same year, the 1998 Farm Bill⁶ directed the Secretary of Agriculture to transform the FIA program into an annual forest inventory and monitoring system. Congress also required development of a detailed strategic plan that describes the process for employing remote sensing in FIA.

After issuing its national framework⁴ for environmental monitoring (CENR 1997), the Office of Science and Technology Policy commissioned the RAND Corporation to analyze operational capabilities in the U.S. for remote sensing in forestry⁷. The resulting report by Peterson and others (1999) acknowledges the importance of FIA as the Nation's premier program for forest inventory and

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² <http://fia.fs.fed.us/>

³ <http://fia.fs.fed.us/library/bluerib.pdf>

⁴ <http://www.epa.gov/cludygxb/Pubs/framework.wp5>

⁵ <http://fia.fs.fed.us/library/brp2.htm>

⁶ Agriculture Research, Extension, and Education Reform Act of 1998, Public Law 105-185, <http://www.reeusda.gov/1700/legis/areera.htm#s253>

⁷ <http://www.rand.org/publications/MR/MR1111.0/>

monitoring with ground measurements. However, RAND found a “widespread perception that existing efforts and capabilities for monitoring...America’s forest resources are failing to meet increasingly complex and broad-scale forest management needs.” RAND went on to note that national assessments for the Government Performance and Results Act⁸, the Montreal Criteria and Indicators, and other international initiatives require a “more ambitious and qualitatively different measurement system than currently exists.” According to RAND, institutional barriers slow the development of this system, and significant institutional changes are needed. RAND specifically identified improvements through better management and integration of existing programs, such as FIA, the Gap Analysis Program⁹ (GAP), the National Resources Inventory¹⁰, and the Multi-Resolution Land Characteristics¹¹ (MRLC) program. RAND suggested that use of remote sensing by FIA for stratification is likely to stimulate operational applications of remote sensing to other forest monitoring efforts, and basic classification of forest conditions with remotely sensed data would offer significant opportunities for coordination, integration, and cost-sharing among Federal programs. RAND concluded that Federal authorities must make a long-term commitment to ensure that forest conditions be periodically mapped by FIA and MRLC using consistent methods.

Later that year, Van Deusen and others (1999) gave a users’ perspective on the role of remote sensing in the annual FIA system. They reaffirmed the importance of FIA field plots as ground truth for remote sensing and precise measurements of tree and stand attributes. However, they predicted “today’s system of placing one plot every...6,000 acres and making little use of satellite remote sensing will seem extravagant in the future.” They suggested that progress is hindered by the lack of an FIA vision for operational remote sensing. Such a vision might lead to “radical changes in the FIA system and yield significant improvements in information quality and cost-effectiveness.”

In 2000, the national FIA program articulated this vision for operational use of satellite remote sensing (Guldin 2000)¹².

⁸ <http://www.fs.fed.us/plan/>

⁹ <http://www.gap.uidaho.edu/>

¹⁰ <http://www.nhq.nrcs.usda.gov/NRI/>

¹¹ <http://landcover.usgs.gov/natl/landcover.html>

¹² <http://fia.fs.fed.us/library/RS2000.rtf>

The FIA vision is deeply rooted in recommendations from the Second Blue Ribbon Panel³ (AFPA 1998) and the national technology assessment conducted by RAND⁷ (Peterson and others 1999). Guldin emphasized the emerging importance of geospatial data: “the key analytical outputs today are maps, map layers, or other spatial representations of information and complex (spatial) models.” This is a paradigm shift for FIA, in which new geospatial products join with traditional FIA statistical products for the comprehensive inventory and analysis of the Nation’s forests and rangelands. FIA will use remote sensing technologies not only to improve statistical efficiency through stratification, but also to map the Nation’s forest conditions in support of broad-scale geospatial analyses.

Guldin also offered an ambitious performance target for implementation of this vision: FIA will complete the transition to satellite imagery by the end of 2003. Specifically, FIA will rely on satellite imagery to produce area estimates, including estimates for small geographic areas; produce accurate, high resolution, remotely sensed maps of forest attributes; and enable a wide variety of spatial analyses by linking satellite imagery to the spatial data in the FIA database. FIA will map 15 to 20 major forest cover types at the national to regional levels. Further refinements may be important below the regional level. The image processing process will be highly automated to reduce cost. High-resolution geospatial data from other sources will improve geospatial modeling and accuracy assessments. Small-area models will interpolate FIA ground data for each 30-m pixel using techniques such as the “k-Nearest Neighbor” method (e.g., McRoberts and others, this volume). This vision includes the capability to combine data from various programs to more effectively answer a much broader range of analyses than any agency could achieve alone. The outcome will be consistent, multi-scale geospatial data for all parts of the U.S.

EVOLUTION OF A PARTNERSHIP

In 1992, the USGS EROS Data Center (EDC) helped form a national consortium of Federal programs to build a library of Landsat-5 imagery that covers the U.S. This Multi-Resolution Land Characteristics¹³ (MRLC) consortium includes the EPA Environmental Monitoring and Assessment Program¹⁴ and

¹³ http://edcwww.cr.usgs.gov/glis/hyper/guide/old_mrlc

¹⁴ <http://www.epa.gov/emap/index.html>

the North American Landscape Characteristics¹⁵ Project; the USGS National Water-Quality Assessment Program¹⁶ and GAP Program⁹; the NOAA Coastal Change Analysis Program¹⁷ (C-CAP); and the USDA Forest Service. The consortium purchased 680 Landsat scenes for the conterminous U.S.¹³.

In 1995, EDC facilitated a second cost-sharing partnership to produce the National Land Cover Dataset¹³ (NLCD-1992). NLCD-1992 is a set of consistent land cover maps at 30-m spatial resolution for the entire Nation (Vogelmann and others 2001). NLCD-1992 is derived from Landsat-5 scenes for approximately 1992 that were purchased by the MRLC consortium¹³. The NLCD partnership serves business needs for three consortium members: EDC, EPA¹⁴, and NOAA¹⁷. NLCD-1992 replaces the land use and land cover maps developed by USGS in the 1970s and 1980s from high-altitude aerial photography.

At 30-m spatial resolution, NLCD supports geospatial analyses that require more spatial detail than coarse-scale global datasets (e.g., 1-km spatial resolution of the AVHRR satellite) but that extend across broad geographic areas that are too large to practically process with very fine-scale datasets (e.g., 4-m or less spatial resolution). Suitable uses for NLCD can include broad-area assessments and national analyses of wildlife habitat, wildfire hazards, priorities for forest fuel treatments, risks from insects and disease impacts to forests, landscape patterns, and ecosystem health (Vogelmann and others 2001). Analyses for a small area (e.g., a county) are not recommended with NLCD because it is nearly impossible to ensure sufficient accuracy of a national product for each local area. Errors in NLCD at the local level can “average out” when analyzing larger areas, without major distortions to broad-scale spatial patterns.

NLCD uses 21 classes of land cover based on the Anderson Level II¹⁸ and C-CAP systems¹⁷. Upland forest is separated into deciduous, evergreen, and mixed forest. There are categories for woody wetlands, shrublands, and grasslands; two water classes; three barren classes; three urban classes;

six agricultural classes; and an emergent wetland class. At this level of detail, classification accuracy is around 60 percent but increases to 80 percent for aggregations of land types to Anderson Level I¹⁹ (Yang and others 2001). Modifying the spatial resolution from a 30-m pixel to a larger element (e.g., a 3 X 3 pixel cluster) also improves accuracy.

Soon after completion of NLCD-1992, FIA scientists began comparing NLCD products to other remote sensing alternatives for stratification of FIA plots. In the Northeast, Hoppus and others (this volume) and Hoppus and Lister (this volume) report that NLCD-1992 produces statistical efficiencies nearly identical to the alternatives. Wayman and others (2001) find there are no significant differences in accuracy between NLCD data and alternative Landsat products, although traditional FIA photointerpretation is more accurate and produces more precise statistics. Dunham and others (2003) report that NLCD is very efficient because development costs are divided among many agencies. In the Pacific Northwest, Dunham and others (this volume) find that stratification based on NLCD sacrifices little precision in inventory estimates, although no alternative, including traditional FIA photointerpretation, completely satisfies FIA targets for statistical precision. At the same time, FIA began to work with other agencies to use NLCD-1992 to build a national geospatial database containing indicators of landscape conditions, including spatial patterns of forest cover (Riitters and others 2000)²⁰. These are useful in large-area ecological assessments and national-scale modeling of biogeographic and socio-economic phenomena.

In 1999, NASA launched Landsat-7. Its new Enhanced Thematic Mapper (ETM+) is a substantial technological advancement (Goward and others 2001) over Landsat-5, which was the basis for NLCD-1992. Almost immediately, the MRLC-2000²¹ consortium formed to share costs for a new collection of Landsat-7 imagery. Based on experiences with NLCD-1992, EDC made significant improvements to MRLC-2000 procurement specifications. Three seasons of imagery are being selected for every path/row: early season (green up), peak greenness (summer), and late season

¹⁵ <http://www.epa.gov/nerlesd1/land-sci/north-am.htm>

¹⁶ <http://water.usgs.gov/nawqa/>

¹⁷ http://www.csc.noaa.gov/crs/ccap_index.html

¹⁸ <http://landcover.usgs.gov/classes.html>

¹⁹ Forest, water, urban, barren land, agricultural land, wetland, and rangeland

²⁰ <http://www.srs.fs.fed.us/4803/landscapes/index.html> and <http://www.esapubs.org/archive/ecol/E081/004/metadata.htm>

²¹ <http://edcw2ks15.cr.usgs.gov/lccp/mrlc2k/mrlc2k.asp>

(brown up). Target dates for each image are optimized based on analyses²² of AVHRR bi-weekly data and NLCD-1992. MRLC-2000 data are terrain-corrected and re-sampled for an average registration accuracy of 1-pixel, which expedites overlays of MRLC and NLCD products for 1992 and 2000. Data are available to any partner agency for \$45 per CD without restrictions for non-commercial applications²¹. FIA joined the consortium in 2001.

At that same time, land cover maps from NLCD-1992 were quickly becoming outdated; technologies for land cover classification had improved; and the transition by FIA to annual surveys improved the value of FIA ground plots as training sites and accuracy assessment data for remote sensing. EDC approached potential Federal partners to build NLCD-2000 based on new Landsat-7 data. NLCD-2000 includes radiometric calibrations²² that provide seamless data across scenes. NLCD-2000 uses regression models that predict tree canopy density from Landsat data; 1-m resolution satellite data are used to develop these regression models. NLCD produces an index of spatial texture that uses spectral variability among contiguous pixels, and NLCD uses image segmentation to produce additional indices that describe land cover patterns (McGarigal and Marks 1995, Gustafson 1998). A 30-m Digital Elevation Model provides information on elevation, aspect, slope, and position of the pixel on the slope. National STATSGO soil maps supply coarse-scale indices of available water capacity, soil organic carbon, texture, and depth. All of these ancillary data help separate different land cover types that have similar spectral signatures. While NLCD-1992 produced only a national map of land cover, NLCD-2000 will provide a nationwide geospatial database for land cover and forest type classifications plus the ancillary geospatial data used to build those classifications.

Early in 2001, a team of FIA and EDC scientists began testing the value of FIA plots as training data for NLCD-2000. Chengquan and others (this volume) report results for study areas in the east coast and the Rocky Mountain regions. They found that FIA plot data are useful for training data and accuracy assessments. They separated forest from nonforest cover with 80-90 percent accuracy; deciduous, evergreen, and mixed forest with 79-83 percent accuracy; and achieved 66 percent overall accuracy for more detailed forest types²³. They conclude that FIA plot data can

substantially improve efficiency, accuracy, and consistency. FIA field plots also statistically describe the composition of each forested map class in a broad region (e.g., distribution of stem densities by tree species and size class; median crown bulk density; range of stand ages; average wood volume per acre; average tree mortality rates; average fuel loading; and so on).

In 2002, FIA recognized that joining the NLCD-2000 consortium could help FIA reach its performance target for operational remote sensing. The extensive mapping infrastructure already developed at EDC could become the Nation's "assembly line" for remotely sensed maps of forest conditions, and FIA could share the \$10 million cost of NLCD-2000 with other consortium members. This would allow FIA to serve a much broader range of spatial analyses in forestry than it could accomplish alone.

BENEFITS TO FIA CUSTOMERS

The Forest Service and other agencies conduct broad-area assessments using geospatial models that require data with fine spatial resolution. Current assessments are constrained by lack of consistent fine-resolution geospatial data that cover entire provinces, multiple states, and the Nation. NLCD-2000 will improve this situation because it will contain nationally consistent data on land cover and forest conditions, terrain, soils, climate, and potential natural vegetation. These data themes are at the core of many geospatial models for forest lands. For example, when the Western Governors' Association (2001) released its national strategy²⁴ to address catastrophic wildfires, new geospatial models were needed to assess communities at risk; current vegetative conditions with respect to likelihood of severe wildland fire; and threats to local economies, key habitats, air quality, and water quality (e.g., post-fire erosion). Such broad-scale analyses identify high-priority geographic areas

²² <http://landcover.usgs.gov/publications.html>

²³ This level of classification detail meets the FIA vision for remote sensing (Guldin 2000); detailed forest types for mapping included spruce/fir, loblolly & shortleaf pine, oak/pine, oak/hickory, oak/gum/cypress, elm/ash/red maple (i.e., six types) in the mid-Atlantic region; and pinyon/juniper, Douglas-fir, ponderosa pine, fir/spruce/mountain hemlock, lodgepole pine, other western softwoods, aspen/birch, western oak, other western hardwoods (i.e., nine types) the Rocky Mountains.

²⁴ <http://www.westgov.org/wga/initiatives/fire/>

for more intensive analysis and management. As inputs to those models, the geospatial database must have detailed maps for vegetation type, forest structural-stage, stand density, and other physiographic and ecological attributes. FIA participation in NLCD-2000 could increase quality of such data, and thus indirectly improve the cost-effectiveness of reducing wildland fire risks to communities and the environment.

FIA plot data could increase the value of NLCD-2000 to other Federal efforts that use geospatial data on forest conditions to predict risks from insects and diseases, habitat suitability, and other forestry applications. FIA could use its ground data with remotely sensed data to map more detailed attributes of forest stands, such as 30 to 50 different forest types, stand density, stand structure, and potential fuel loading. This could be accomplished with statistical techniques such as the “k-Nearest Neighbor” procedure discussed by Guldin (2000) and illustrated by McRoberts and others (this volume). Other programs would not have access to FIA plot coordinates, but they would have access to high-quality, detailed maps of forest conditions that were produced with FIA ground plots. The responsibility of FIA would end at the production of forest condition maps, and other programs would assume responsibility for application of those maps in their own analyses and management decisions. As the value of NLCD-2000 products increases, so does the motivation for more partners to share costs. This improves program efficiency, product delivery, and data consistency for each partner. Potential partners include State agencies, the USDA National Resources Inventory¹⁰, EPA^{14,15}, NOAA¹⁷, and other USGS programs^{9,16}.

NLCD is optimized for broad-area assessments, ranging from provincial to national levels. This does not reduce the importance of specialized geospatial products for “local” areas (e.g., a national forest). Local products are optimized to satisfy local analysis requirements; they benefit from local knowledge and acceptance; and they are less prone to confounding variability across space and Landsat scene dates. Since management decisions occur at all spatial scales, an integrated system should be developed that allows for multi-scale analysis. Local decisions need to be analyzed within a broader geographic context. The database philosophy adopted in NLCD-2000 allows local users to derive land cover products tailored to their specific

applications²⁵, and local users can identify cases in which a national product needs improvements in certain locations. However, further integration is possible.

RISKS TO THE FIA PROGRAM

While a partnership with the NLCD-2000 consortium directly serves FIA objectives, there are also risks. The primary value of FIA plots for remote sensing operations is automated “training” of digital statistical algorithms. These algorithms are the basis for statistical prediction of forest conditions in each pixel. Exact coordinates of each FIA ground plot are used to accurately register that plot to its corresponding cluster of Landsat pixels. Those coordinates must be stored at EDC because FIA does not have sufficient infrastructure to process such massive geospatial datasets. However, disclosure²⁶ of exact FIA plot coordinates is controlled under the Food Security Act of 1985 (as amended) to protect landowner privacy, guard the long-term integrity of the FIA ground sample, and maintain the FIA reputation for providing unbiased information. FIA has never shared with any external partner the exact coordinates for all 120,000 forested FIA ground plots in the USA. If EDC were to disclose those coordinates, then the very foundation of the national FIA program could crumble. This dire consequence, even if very unlikely, poses great risks to FIA. However, there are techniques to manage those risks. An FIA scientist stationed at EDC could monitor security of FIA coordinates. The amount of FIA data residing in EDC at any one time could be minimized. FIA coordinates could be immediately purged from the EDC database when no longer needed in the production process. A culture and code of ethics could be fostered at EDC that recognizes their obligations as “duly authorized agents” of the FIA program under its privacy and confidentiality policy²⁶. A formal agreement between FIA and EDC could precisely specify roles, responsibilities, authorities, and expectations of each partner.

²⁵ http://landcover.usgs.gov/natlandcover_2000.html

²⁶ By law, any person who publicly discloses exact coordinates of FIA plots will be fined not more than \$10,000 or imprisoned for not more than 1 year, or both. <http://fia.fs.fed.us/library/privacy.htm>

THE DECISION

In January 2002, FIA decided, in principle, to join the NLCD-2000 consortium and use FIA ground plots to improve mapping of 15 to 20 forest types across the Nation. This begins the operational remote sensing component of FIA, thus accomplishing its 2003 performance target. As the benefits of this strategy materialize, FIA may expand its suite of remotely sensed products to include forest structure, volume, and other important forest attributes. Now, FIA has a preeminent role in the comprehensive mapping and analysis of the America's forests. Preeminence does not connote dominance, but it does mean an essential role within a multi-agency team that shares resources and creates a superior product for the Nation.

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A COMPARISON OF STRATIFICATION EFFECTIVENESS BETWEEN THE NATIONAL LAND COVER DATA SET AND PHOTOINTERPRETATION IN WESTERN OREGON

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ABSTRACT.—Stratifications developed from National Land Cover Data (NLCD) and from photointerpretation (PI) were tested for effectiveness in reducing sampling error associated with estimates of timberland area and volume from FIA plots in western Oregon. Strata were created from NLCD through the aggregation of cover classes and the creation of 'edge' strata by reclassifying pixels at class boundaries. Strata were created from aerial photography by interpretation of a sample grid for land use and cover attributes. NLCD-based stratifications are less costly than PI and sacrifice little precision on inventory estimates. Neither PI nor NLCD stratifications achieved the FIA target of 10 percent sampling error/billion cubic feet of volume, but both are near the national standard of 3 percent sampling error/million acres of timberland.

Timberland² area and growing-stock volume³ on timberland are two of the key forest resource estimates that the Forest Inventory and Analysis (FIA) program of the USDA Forest Service is mandated to produce. National accuracy standards are in place for sampling error of timberland area and growing-stock volume. In the Pacific Northwest (PNW), the maximum allowable error for timberland area is 3 percent sampling error per million acres of timberland. For growing-stock volume on timberland in PNW a target of 10 percent sampling error per billion cubic feet "...to be achieved as closely as practicable" is specified (Forest Service Handbook 1967). Due to constraints of time, resources, and budget, it has never been possible to meet these standards in PNW through the use of plot data alone. FIA, both nationally and at PNW, has long relied on two-phase sampling (Cochran 1977) to increase precision of inventory estimates. A relatively

inexpensive data collection effort based on remotely sensed data (phase 1) serves as a stratification for expensive-to-collect plot data (phase 2). Stratified sampling is a more cost-efficient approach to reducing the sampling error associated with inventory estimates than increasing sample size.

The following equation converts observed sampling error (in percent) to a percent sampling error per specified area or volume (Hansen 2000).

$$E_s = \frac{(E_o) \sqrt{\text{Estimated total volume or area}}}{\sqrt{(\text{Specified volume or area})}}, \quad (1)$$

where,

$$E_o = \frac{(\text{Standard Error})}{\text{Estimate}} \quad (2)$$

E_s = sampling error in percent for the specified area or volume

When evaluating timberland area, the specified area is 1 million acres and an E_s of < 0.03 is mandated; for growing-stock volume, the specified volume is 1 billion cubic feet and an E_s of < 0.10 is desired.

For this study we evaluated stratifications based on two data sources for phase 1. Evaluation was based on cost and effectiveness in reducing the sampling error of estimates of timberland area and of growing-stock volume on timberland.

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² Timberland = Forest land capable of growing 20 cubic feet or more per acre per year at culmination in fully stocked, natural stands of continuous crops of trees to industrial roundwood size and quality.

³ Growing-stock volume = Net volume in cubic feet of live sawtimber and poletimber trees of commercial species and less than 75 percent cull, from a 12-inch stump to a 4-inch top.

The first phase 1 data source was the traditional FIA approach of using a photointerpreted grid; the second data source was the use of the National Land Cover Data set (NLCD) GIS layer for phase 1. The inventory estimates used for testing were timberland area and growing-stock volume on timberland.

STUDY AREA

The study area is approximately 11 million acres in size and consists of the Oregon counties west of the crest of the Cascade Range plus Hood River County, but excludes lands administered by the Forest Service and Bureau of Land Management. Approximately two-thirds is forested; over 90 percent of the forest is classified as timberland and over 50 percent of the timberland is dominated by Douglas-fir (*Pseudotsuga menziesii*).

DATA

Phase 2 Data (Field Plots)

For this study 1,449 plots visited by FIA crews between 1995 and 1997 were used. FIA field plots were on a nominal 3.4-mile grid; each plot consists of five subplots dispersed over a 5.2-acre area. At each plot, the proportion of plot area by land use (timberland, non-productive forest, or nonforest) was assessed. Where plots were at least partially forested, attributes such as percent forest, percent timberland, and area by forest type (predominant overstory species) were assessed. Trees occurring on forested subplots were measured.

Phase 1 Data (Photointerpretation)

A 0.84-mile grid of phase 1 photoplots was established on 1994 vintage 1:40,000 scale black and white aerial photo transparency stereo pairs. To ensure that photoplots were established at locations corresponding to their true coordinates, digitizing photogrammetry software was used to compensate for scale and parallax effects (Warner and Carson 1992). Within the study area there were 23,480 photoplots. At each photoplot, attributes such as land use, crown cover, broad forest type (conifer vs. hardwood), stand stage of development, and conifer height classes were assessed for a 5.2-acre circle⁴. Approximately 6 percent of these photoplots were also measured as phase 2 field plots on the ground.

Phase 1 Data (National Land Cover Data Set)

The National Land Cover Data set is a land cover GIS layer developed by the United States Geological Survey (USGS) from leaf-on and leaf-off LANDSAT 5 TM imagery circa 1992. This layer was derived primarily through the unsupervised classification of the imagery and through the use of ancillary spatially referenced data such as elevation, population density, soil attribute maps, and National Wetlands Inventory data. The resulting data set is a land cover map for the conterminous U.S. with 30-m resolution and 21 cover classes (Vogelmann and others 2001). Accuracy assessment was conducted by the USGS based on interpretation of 1990 National Aerial Photography Program photographs. Overall accuracy at Anderson Level 1 classification was 81 percent for the United States east of the Mississippi and Ohio Rivers, but it dropped to 60 percent for the 21 individual classes (Vogelmann and others 2001). Accuracy assessment has not yet been completed for the western U.S.

METHODS

Stratification by Photointerpretation

In the testing of photointerpreted data as the phase 1 sample, photoplots and their associated field plots were grouped into strata based on similarity of photointerpreted attributes. Stratum areas were calculated by assigning fractions of the total sample area in proportion to the number of photoplots within each stratum. Population totals and variances were calculated for timberland area and growing-stock volume using equations for double sampling for stratification (Cochran 1977). It should be noted that this stratification technique does not produce a map of the strata; the size of the strata can be calculated but their boundaries cannot.

Two stratifications were developed and tested from the photointerpreted phase 1 data. The first stratification (PI-Area) was designed to provide the most precise estimate of timberland area. Each photoplot was assigned to a stratum based on the proportion of the photoplot that was interpreted to be timberland. Twelve strata were created in this manner, ranging from 0 percent to 100 percent timberland. The

⁴ A procedures manual entitled "Instructions for Western Oregon Primary Sample Data Collection" is on file with the USDA Forest Service, Pacific Northwest Research Station, Portland, OR.

second stratification (PI-Volume) was designed to provide the most precise estimate of growing-stock volume. Photoplots were assigned to strata based on interpretation of land use (timberland, non-productive forest, or nonforest), broad forest type (conifer, hardwood, or nonstocked), crown closure, conifer heights, and stage of stand development (nonstocked, seedling-sapling, poletimber, or sawtimber).

Stratification by NLCD

When testing NLCD as the phase 1 sample, we made several changes to the GIS layer to match FIA land use definitions and to eliminate unnecessary classes. Of the 21 NLCD classes, 6 corresponded generally to what FIA would define as forest in western Oregon: deciduous forest, evergreen forest, mixed forest, woody wetlands, shrubland, and transitional. The other NLCD classes were aggregated into a single nonforest class. The shrubland and transitional classes were included as possible forest because these areas are often recent clearcuts where forest is expected to regenerate. Three groupings of these classes were tested as the basis for stratification. The first grouping (forest/nonforest) was a simple forest versus nonforest two-class scheme where all six potential forest classes were combined into the forest class. The second grouping (forest/other-forest/nonforest) combined the classes most likely to be timberland (deciduous forest, evergreen forest, and mixed forest) into the forest class; the transitional, shrubland, and woody wetland classes were combined into another forest class (three classes). The third grouping (deciduous/evergreen/mixed) used deciduous forest, evergreen forest, mixed forest, other forest, and nonforest as separate classes (five classes).

Areas smaller than FIA's minimum mapping requirements (less than an acre, equivalent to four 30-m pixels of the same class) were re-assigned to adjacent classes. This was accomplished using the clump, sieve, and neighborhood functions of ERDAS Imagine (ERDAS 1997).

Following Hansen (2000), we investigated the effectiveness of using edge strata for each of the three class groupings. Edge strata were created at the margins of each class using a search function (ERDAS 1997). In cases where registration or coordinate errors cause a field plot to be assigned to the wrong stratum or where a field plot overlaps class boundaries, the anomalous value contributed by that plot can substantially increase the variance of the stratum associated with that plot. Edge strata allow these field plots to be isolated within

smaller strata where they will have less impact on the overall variance. The width of edge strata tested ranged from 2 to 4 pixels (60 to 120 m).

Stratum sizes were calculated by summing pixel counts within each stratum with each pixel counting as 0.22239 acres. Population totals and variances were calculated for timberland area and growing-stock volume using equations for stratified estimation (Cochran 1977).

No Stratification

As a basis for comparison, timberland area and growing-stock volume were also summarized using no stratification. Population totals and variances were calculated using equations for a simple random sample (Cochran 1977).

RESULTS

Timberland Area

Both photointerpretation stratifications met the FIA standard for 3 percent sampling error per 1 million acres of timberland. Performance of the PI-Volume and PI-Area stratifications was nearly equal: each reduced the sampling error by just over 40 percent compared to a random sample (no stratification). In this situation, stratification designed for volume on timberland (PI-Volume) was also effective as a stratification for timberland area (table 1).

None of the stratifications based on NLCD met the 3 percent standard for sampling error; however, the best performers came quite close to the target at 3.2 percent, a sampling error 34 percent lower than the random sample (fig. 1). When edge strata were not used, all three groupings of the forest classes performed about equally with sampling errors of 3.5 percent per million acres. The addition of edge strata improved the performance of the forest/nonforest and the forest/other forest/nonforest groupings, with 4-pixel edges having more benefit than 2-pixel edges. Edge strata had little effect on the deciduous/evergreen/mixed grouping (table 1).

Growing-Stock Volume

Neither photointerpretation based stratification met FIA's 10 percent sampling error per billion cubic feet target, but the stratification intended for volume (PI-Volume) was close at

Table 1.—Timberland area in western Oregon by stratification technique (outside national forests and Bureau of Land Management lands)

Stratification method	Area in millions of acres	Standard error in millions of acres	Sampling error per million acres
No stratification	6,981	128	4.9%
Forest/Nonforest no edge	6,887	93	3.5%
Forest/Nonforest 4-pixel edge	6,982	85	3.2%
Forest/Other forest/Nonforest no edge	6,891	92	3.5%
Forest/Other forest/Nonforest 4-pixel edge	6,991	85	3.2%
Deciduous/Evergreen/Mixed no edge	6,895	91	3.5%
Deciduous/Evergreen/Mixed 4-pixel edge	6,955	89	3.4%
PI-Area	7,034	72	2.7%
PI-Volume	7,013	73	2.8%

12.9 percent sampling error per billion cubic feet. The PI-Volume stratification had a sampling error 22 percent lower than that of a random sample (fig. 1).

None of the stratifications based on NLCD met the 10 percent standard, with the best performing NLCD stratification, at 14.1 percent, a little worse than PI-Volume. Unlike NLCD stratification for timberland area, less aggregation of the forest classes led to better results when stratifying for volume (table

2). The deciduous/evergreen/mixed grouping worked well for volume stratification, most likely because of the large difference in growing-stock volume between conifer and hardwood stands represented by the evergreen and deciduous forest classes, and the inclusion of recently clearcut timberland in the other forest class. The addition of edge strata improved the performance of all three of the forest groupings with the most benefit coming from the widest edge strata. The best performing NLCD stratification for volume was the

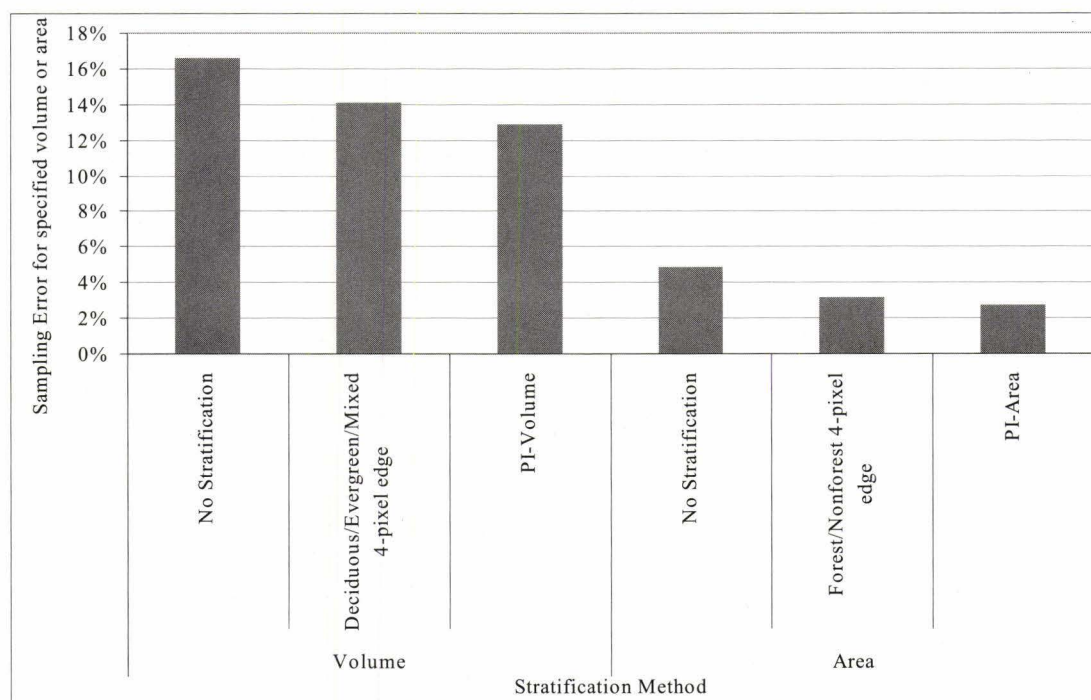


Figure 1.—Sampling error per million acres of timberland or billion cubic feet of growing-stock volume for no stratification, best NLCD stratifications, and best photointerpreted stratifications.

Table 2.—Growing-stock volume in western Oregon by stratification technique (outside national forests and Bureau of Land Management lands)

Stratification method	Volume in million cubic feet	Standard error in million cubic feet	Sampling error per billion cubic feet
No stratification	20,046	742	16.6%
Forest/Nonforest no edge	19,729	668	15.0%
Forest/Nonforest 4-pixel edge	20,055	648	14.5%
Forest/Other forest/Nonforest no edge	19,743	658	14.8%
Forest/Other forest/Nonforest 4-pixel edge	20,207	637	14.2%
Deciduous/Evergreen/Mixed no edge	19,874	657	14.7%
Deciduous/Evergreen/Mixed 4-pixel edge	20,046	632	14.1%
PI-Area	20,150	628	14.0%
PI-Volume	20,440	582	12.9%

deciduous/evergreen/mixed grouping with 4-pixel edges. This stratification achieved a 15-percent reduction in sampling error compared to a random sample (fig.1).

DISCUSSION

Although stratification using NLCD brings less reduction in sampling error than stratification using photointerpretation, it can be accomplished at a fraction of the cost (table 3). The photointerpretation of western Oregon required a large investment to purchase 2,400 aerial photos, establish the sample points on the photos, develop sampling protocols, and interpret the photography. The NLCD approach achieves

nearly as much reduction in sampling error at one-twentieth the cost of stratification by photointerpretation. At least for western Oregon, NLCD appears to be a very attractive stratification alternative to traditional methods.

Other factors besides cost and precision can influence choice of stratification approach. Aerial photography has a much finer resolution than NLCD and can be used for applications other than stratification. For example, PNW-FIA has used the photography purchased for stratification as a data source for analysis of land development over time, including change in structure counts on photography from three decades (Azuma and others 1999). The NLCD approach works reasonably well as a stratification tool in western Oregon where the vast

Table 3.—Cost comparison of stratification methods

Stratification method	Estimated cost per million acres	Study area size in acres	Total cost to stratify study area
Photointerpretation			
Photo Acquisition	\$ 1,945		
Photo Setup	\$ 14,140		
Photointerpretation	\$ 2,203		
Total	\$ 18,288	11,090,003	\$ 202,814
NLCD			
Reproject, mosaic & mask	\$ 251		
Classify/post-process filtering/edging	\$ 503		
Administration/coordination	\$ 101		
Total	\$ 854	11,090,003	\$ 9,471

majority of forest land has a high degree of tree crown cover. It is unlikely that NLCD alone would work well in areas where forest typically has low crown cover that may go undetected by satellite imaging. For example, of the 2.8 million acres of juniper forest in eastern Oregon nearly half has crown cover less than 20 percent (Gedney and others 1999). The cost advantages of the current NLCD version are due to the high degree of subsidy in its development and the sharing of cost between agencies. As new versions are developed (one is planned based on year 2000 imagery), FIA may be asked to bear more of the cost of its development. The cost of stratification using NLCD may increase with newer versions but is not expected to approach the cost of photo-interpretation. At this time it is unknown how long the NLCD product based on 1992 imagery will remain an effective Phase 1 data source.

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EFFICIENCY AND PRECISION FOR ESTIMATING TIMBER AND NON-TIMBER ATTRIBUTES USING LANDSAT-BASED STRATIFICATION METHODS IN TWO-PHASE SAMPLING IN NORTHWEST CALIFORNIA

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ABSTRACT.—Three Landsat TM-based GIS layers were evaluated as alternatives to conventional, photointerpretation-based stratification of FIA field plots. Estimates for timberland area, timber volume, and volume of down wood were calculated for California's North Coast Survey Unit of 2.5 million hectares. The estimates were compared on the basis of standard errors, conformance to FIA accuracy standards, and gain in precision achieved by stratification relative to simple random sampling and to conventional photointerpretation. Some satellite imagery-based approaches were found to be far less costly than the conventional method, with very little sacrifice in precision.

National forest inventories in the United States, conducted by the USDA Forest Service's Forest Inventory and Analysis (FIA) program, have traditionally relied on two-phase (or double) sampling for stratification. This technique leverages expensive-to-measure data collected from field plots with cheap-to-measure attributes derived from remote sensing imagery to achieve reductions in the variance of the inventory estimates. Cochran (1977) described the underlying theory and Poso and others (1990) applied this theory in a forest inventory using remote sensing as the Phase 1 data source. Chojnacky (1998) described the application of double sampling to FIA inventories.

At the Pacific Northwest Research Station, the FIA unit with responsibility for forest inventory in California, Oregon, Washington, Hawaii, and the Pacific Islands, Phase 1 has long consisted of a primary (0.85 mile) grid of points stratified according to forest characteristics via ocular interpretation of aerial photography. In Phase 2, crews visit a systematic 6-percent sample of the Phase 1 points to install field plots and collect a rich suite of plot and vegetation attributes. Photointerpretation (PI), while less costly than field installation of plots, is still very labor intensive and prone to

producing interpreter-dependent results. Other problems with PI include inconsistent photo quality, cost of photography, logistical challenges of handling and storing large numbers of photographs, and difficulty in ensuring independence between PI and field plot measurement (because interpreters often know which PI points are also field plots) (Hansen 2000). These issues led the FIA program to seek an alternative approach to stratification. Recently, remote sensing techniques and digital data processing hardware and software have developed rapidly. Semi-automated digital remote sensing approaches offer many benefits compared to photointerpretation, such as generating useful maps as byproducts, allowing better understanding of spatial relationships, and permitting capture of data not obtainable via ocular PI; e.g., infrared portions of the spectrum (Congalton and Green 1999).

As with national-scale forest inventories elsewhere, FIA is completing a transition from a primarily timber-focused resource inventory to a multipurpose ecological inventory designed to assess attributes considered essential to more complete characterization of forest habitats and biodiversity. For example, down wood (DW) volume can serve as a useful indicator of biodiversity because it is a measurement with high repeatability and it affects many resource qualities, including species richness, species interactions, and temporal processes (Carroll 1993). An important question then is: Whether, and how much, any kind of stratification improves precision of non-timber attributes? Given that both manual and semi-automated types of approaches rely on classification of

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overstory, we had no basis for assuming that stratification would improve precision for such estimates.

In this study, four stratification approaches were evaluated: three semi-automated approaches based on vegetation estimates derived primarily from Landsat Thematic Mapper (TM) satellite imagery and aerial photointerpretation. The principal hypothesis we sought to evaluate is that one or more semi-automated remote sensing approaches to stratification would yield accuracies comparable to that achieved with a traditional PI, at a reduced cost. We compared precision achieved for selected FIA estimators, time requirements, and the economic considerations implied by the cost of data acquisition, preparation, and analysis. Attributes included timberland area², timber volume on timberland, and volume of down wood (diameter ≥ 5 inches). Indications of precision were obtained by comparing approaches for each attribute the population estimates, standard errors, and the gain in statistical efficiency resulting from stratification (as compared to random sampling). We also compared the degree of conformance with FIA program goals for sampling error for selected variables, where:

$$E_o = \frac{(\text{Standard Error})}{\text{Estimate}} \quad (1)$$

and

$$E_A = \frac{(E_{sp}) \sqrt{\text{Specified volume or area}}}{\sqrt{(\text{Estimated total volume or area})}} \quad (2)$$

where

E_o = observed sampling error

E_A = allowable sampling error

E_{sp} = specified sampling error in percentage at the specified volume or area, which is:

10 percent per 1 billion cubic feet of growing stock on timberland, or

3 percent per 1 million acres of timberland (USDA Forest Service 1967). Observed sampling errors can be converted to a specified area or volume (i.e., 1 million acres or billion cubic feet) basis by using formula 3 (Hansen 2000):

$$E_s = \frac{(E_o) \sqrt{\text{Estimated total volume or area}}}{\sqrt{(\text{Specified volume or area})}} \quad (3)$$

where

E_s = sampling error for the specified area or volume

The most important accuracy requirement in FIA inventory is 3 percent sampling error per 1 million acres of timberland (USDA Forest Service 1967). For total volume on timberland, the goal is 10 percent per 1 billion cubic feet, but this is "error to be achieved as closely as practicable."

STUDY AREA

We selected the field-sampled area of 2.5 million hectares within California's North Coast Survey Unit³ (fig. 1) because there was a recent (1994) FIA inventory data set available for this area and because the vegetation ranges from dense forest to oak woodland and shrub savannah, which makes for a challenging test of the alternative approaches. Three satellite imagery-based vegetation map products were available for this area, which allowed a comprehensive comparison of different approaches.

Dominant forest cover in the timberland portions of the study area consists of redwood (*Sequoia sempervirens*), Douglas-fir (*Pseudotsuga menziesii*), and tanoak (*Lithocarpus densiflorus*) with white fir (*Abies concolor*), grand fir (*Abies grandis*), ponderosa pine (*Pinus ponderosa*), sugar pine (*Pinus lambertiana*), Pacific madrone (*Arbutus menziesii*) and California black oak (*Quercus kelloggii*) accounting for most of the rest of the trees (Waddell and Bassett 1996). Elevation ranges from sea level to > 2,000 m, and precipitation ranges from 0.6 to 3.2 m per year.

METHODS

Data Sources

Four different vegetation coverage datasets were used in the study. In the first one, ocular PI was applied. Classifications of Landsat TM satellite imagery into vegetation cover types

² Timberland is forest land capable of growing continuous crops of trees to industrial roundwood size, quality, and quantity, with a mean annual increment of 1.4 m³/ha/year at culmination; forest land is, or has been and is likely to be again, at least 10 percent stocked by trees and is not converted to nonforest use (Phillips 1991).

³ Consists of 6.2 million acres of private and non-reserved public lands outside of national forests and national parks in the counties of Del Norte, Humboldt, Mendocino, and Sonoma (Waddell and Bassett 1996) (fig. 1).

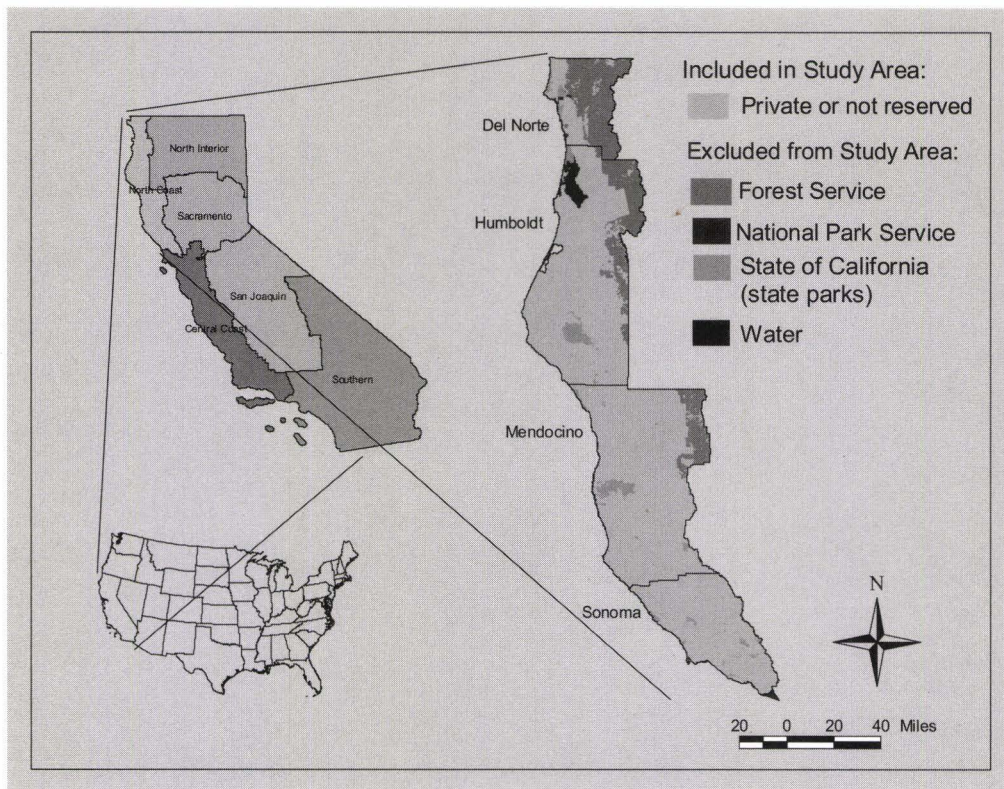


Figure 1.—Land ownership in the North Coast Survey Unit of California.

were at the core of all three semi-automated stratification approaches. In all three cases, 30-m Landsat TM images from the early 1990s were used.

FIA Data

Ocular PI of 10,691 points on 1:32,000 scale, 1988 vintage black and white photography was performed by four interpreters for the study area in 1991. The information interpreted for a 5-acre circle around each PI point included forest land stratum (FLS) (with 16 possible classes based on productivity and crown closure), crown cover (percent), stage of stand development, and plant community (Phillips 1991).

Field plots, which were installed on a 3.4-mile square grid, consisted of clusters of five variable-radius subplots, inscribed within a 2.5 ha circle, on which trees > 5 inches d.b.h. were assessed for a rich suite of attributes, including size (d.b.h., h), species, and timber quality (crown ration etc.). Understory vegetation, seedlings, and saplings were assessed on smaller areas within subplots, and down wood was sampled on three transects per subplot.

Classification and Assessment with Landsat of Visible Ecological Groupings

The CALVEG (Classification and Assessment with Landsat of Visible Ecological Groupings) GIS coverage⁴ (figs. 2 and 3) is essentially a modeled vegetation typing (5-ac minimum mapping unit (MMU)) generated from Landsat imagery, unsystematic, non-random field observations of vegetation, DEM-estimated elevation, slope and aspect, and the expert opinion of local forest managers. The modeling is highly localized, with over 100 variants needed to cover the whole state. Validation is based on FIA plot data and both error matrix and fuzzy set approaches (FIA User's Guide 2001).

National Land Cover Dataset

The NLCD (National Land Cover Dataset) GIS layer⁵ (figs. 2 and 3) was modeled via unsupervised classification of terrain-corrected, 1992 vintage Landsat 5 TM imagery from

⁴ Provided *gratis* by the Remote Sensing Lab at the USDA Forest Service, Pacific Southwest Region, in Sacramento, CA; available for most of California.

⁵ Available for the lower 48 states from the Multi-Resolution Land Characteristics Consortium (MRLC) at the USGS EROS Data Center, Sioux Falls, SD.

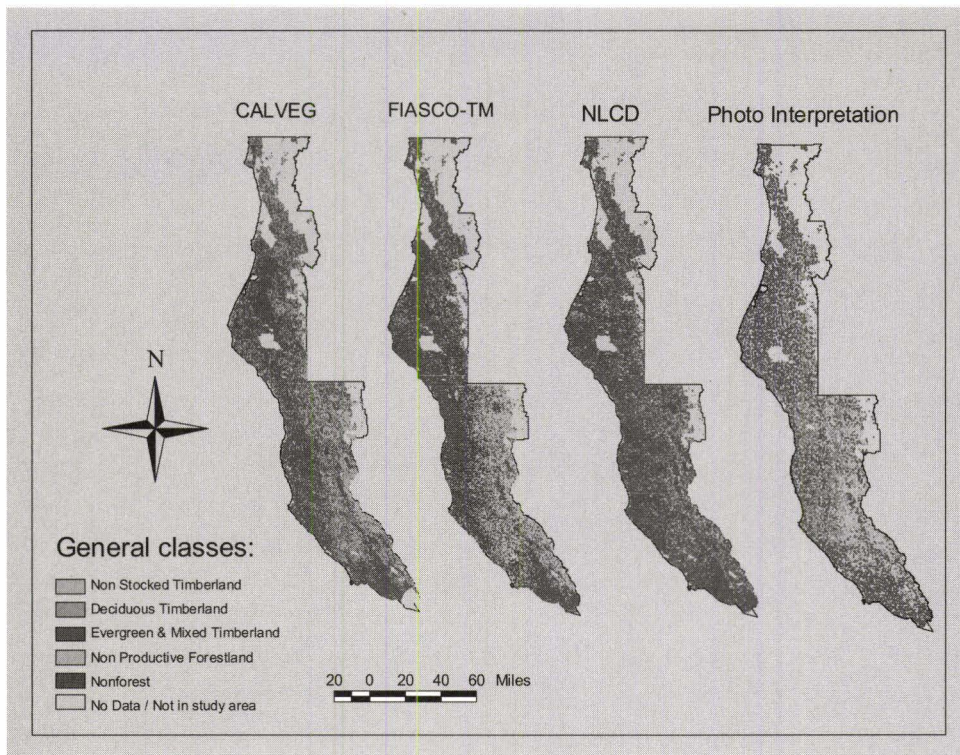


Figure 2.—Forest classification of the four stratification sources tested for the North Coast Survey Unit.

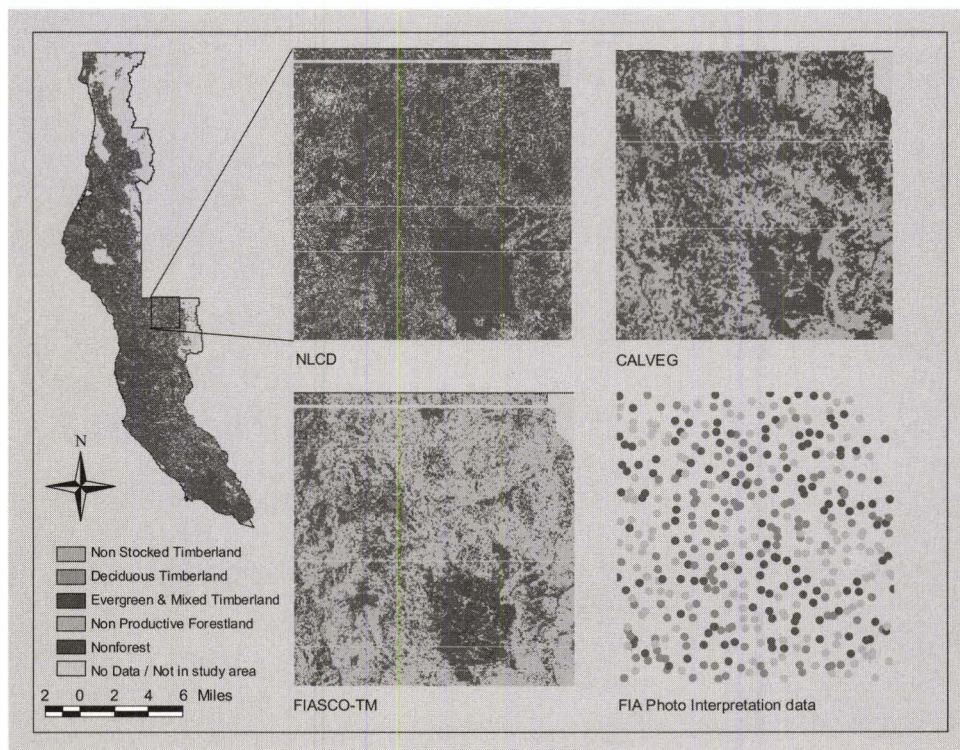


Figure 3.—Fine-scale inspection of the four stratification sources tested reveals effects of differences in class definitions among stratification sources.

at least two different seasons (e.g., leaf-on and leaf-off), census tracts, existing mid-scale cover layers, wetland inventory, and maps of soil attributes (water capacity and organic carbon) (Vogelmann and others 2001). Accuracy assessment was based on interpretations of 1990 National Aerial Photography Program photographs and probability sampling (Vogelmann and others 2001).

Forest Inventory and Analysis Stratification with Classification of Thematic Mapper

The FIASCO-TM (Forest Inventory and Analysis Stratification with Classification of Thematic Mapper) vegetation coverage was constructed via a combination of supervised classification of Landsat TM imagery and a reduced intensity sample of photointerpreted Phase 1 points. The classification program⁶ applied a supervised maximum likelihood classification algorithm, described by Richards (1994) and Campbell (1987), that used a subset of FIA PI points as a training sample. Regions of interest were created around each PI point, and the spectral signatures of these regions were used as seeds for the classes created. Error statistics for the classification were calculated with FIA plot data. The result of the FIASCO-TM classification was a classified raster image (figs. 2 and 3) with error statistics describing the accuracy of the classification. In this study, the Landsat imagery was classified to FIA FLS classes; however, the FIASCO-TM approach could just as easily use any other classification system.

The input to FIASCO-TM consists of georeferenced Landsat imagery, data for the training areas, and plot data for accuracy assessment. Four Landsat scenes for July 1990 covering the North Coast study area were georeferenced, normalized, and mosaicked⁷. Total root mean square error of the georeferencing was close to one-half of the pixel size, which is appropriate for this purpose (ERDAS 1997, Vogelman and others 2001).

⁶ Written in IDL macro language of the ENVI GIS software environment by Dr. Michael Lefsky.

⁷ Using ERDAS Imagine and IDL macro language programs.

⁸ Documentation by Larry Bednar (2001) on file at the USDA Forest Service, Pacific Northwest Research Station, Portland OR.

Sampling Techniques

Alternative stratifications were applied using a SAS-based 'Tabling' application⁸ to generate population estimates and associated variances under three sampling scenarios: double sampling for stratification, stratified random sampling, and simple random sampling (Cochran 1977).

The theory of two-phase sampling is described by Cochran (1977). The technique uses a relatively large sample of more general and cheaper-to-obtain Phase 1 data to divide the population of interest into subpopulations from which the Phase 2 sample is drawn in order to reduce the variance of the population estimates. Based on the values of some variable, the population is stratified into a number of classes. The first sample is a simple random sample; this sample corresponds with PI points in FIA inventory parlance. The second sample can be a subsample from the first sample (e.g., in FIA inventories, field plots are a subsample of PI points), or it can be drawn independently. The cost per sample unit is usually low in Sample 1 compared to Sample 2, and the Sample 2 data are more detailed. When a double-sampling approach is used, the key problem is to choose the size of the samples and the number of sample units in each stratum so that the variance of the estimate is minimized for any given cost.

In stratified sampling a population is divided into subpopulations called strata. When the strata have been determined, a sample is drawn from each. If the sample taken from each stratum is a random sample, the whole procedure is called stratified random sampling. The use of stratification can improve the accuracy of estimates for the whole population. A heterogeneous population can be divided into homogeneous strata based on an attribute thought likely to be related to the attributes for which population estimates are sought, and precise estimates of stratum means can be achieved by drawing a sample from within a stratum. These estimates can then be combined to obtain estimates for the entire population.

Simple random sampling, where no Phase 1 exists and each field plot represents the same proportion of the total population, is considered in this study as the cheapest and most straightforward way to implement a forest inventory.

Sarndal and others (1992) define a stratification design effect—a measure of the gain in statistical efficiency achieved through stratification—as the ratio of the variance with stratification and the variance with simple random sampling. Here, five different levels of design effect were considered, as shown in table 1.

Table 1.—Levels of statistical efficiency used to evaluate the gain of precision via stratification

Design effect (percent)	Level of statistical efficiency
80-100	No effect
67-80	Minimal
50-67	Moderate
25-50	Substantial
0-25	Excellent

The NLCD and FIASCO GIS layers were segmented and sieved (ERDAS 1997) to achieve minimum mapping units consistent with FIA field plot condition mapping rules. In essence, this procedure replaces homogeneous areas smaller than 4 pixels (about 1 acre) with the majority value from surrounding cells.

Areas of forest transition (e.g., from forest to nonforest or from well-stocked to non-productive) typically exhibit greater heterogeneity than pure stands, and such transitions are often so gradual as to make delineation of an exact border challenging. Not surprisingly, such transition zones are loci with a high probability of classification errors resulting from class definitions and layer registration issues. To address these issues, we created edge strata along the edges of productive forest, other forest, and nonforest following an approach pioneered by Hansen (2000). For each Landsat-derived stratification layer, 2-pixel-wide edge classes were created for each of three land classes. Standard errors for timberland area estimates were always lower when edge strata were used, and they were usually lower for timber volume.

Differences in attribute detail and classification systems among the GIS layers meant that each had to be simplified and cross-walked separately, and iteratively, to produce stratification systems capable of near optimal precision gain. Stratification performance was evaluated iteratively, as strata count, edge class configurations, and assorted crosswalk criteria were adjusted by comparing calculated standard errors, conformance to FIA accuracy standards, and design effect for timberland area, timber volume, and DW volume estimates among candidate stratification systems.

Optimizing Precision for Each Stratification System

Two PI-based stratification systems were tested. The “production PI” mimicked the 1994 FIA inventory of the North Coast Survey Unit, for which PI points were divided into groups by FLS code and owner only, and this layer was used to stratify the field plots. Because the available PI data include considerably more detailed information than FLS code alone, and some of this information could considerably improve stratification, a second “optimal PI” stratification system was developed, making use of stage of stand development, plant community, and density information in addition to FLS class. From PI data, we separated all groups that had different combinations of these attributes, and we combined strata that had only a few field plots with the closest remaining stratum. Optimal PI did not improve precision as compared to production PI for timberland area estimates but did for timber volume.

Four stratification systems were tested using the CALVEG GIS layer. One used only the size class information and the second used only density class. Both of these resulted in remarkably high standard errors for timberland area and timber volume because the attributes that were used to define the strata did not form homogeneous classes in terms of these attributes. The third involved a cross-walk from CALVEG to FIA FLS classes that combined vegetation cover type, size, density, and species information in the GIS layer. These strata were much more homogeneous within strata with respect to, for example, plot volume. The fourth added the edge classes (fig. 4) to CALVEG–FLS classification, further reducing the standard error of timberland area but increasing standard error on timber volume estimates.

Following Hansen (2000), segmentation and sieving were applied to transform the NLCD to achieve a MMU of 1 acre, cross-walked to forest and nonforest classes and added forest and nonforest edge classes (designated “fnf”) (fig. 4). This reduced standard errors for timberland area estimates compared to stratifications based on the stock NLCD GIS layer. Recoding the NLCD GIS layer to three classes: forest, other forest,⁹ and nonforest, and building edge classes for each (“fofnf”), improved precision for timber volume estimates.

⁹ Below a productivity threshold implied by the cover type designation.

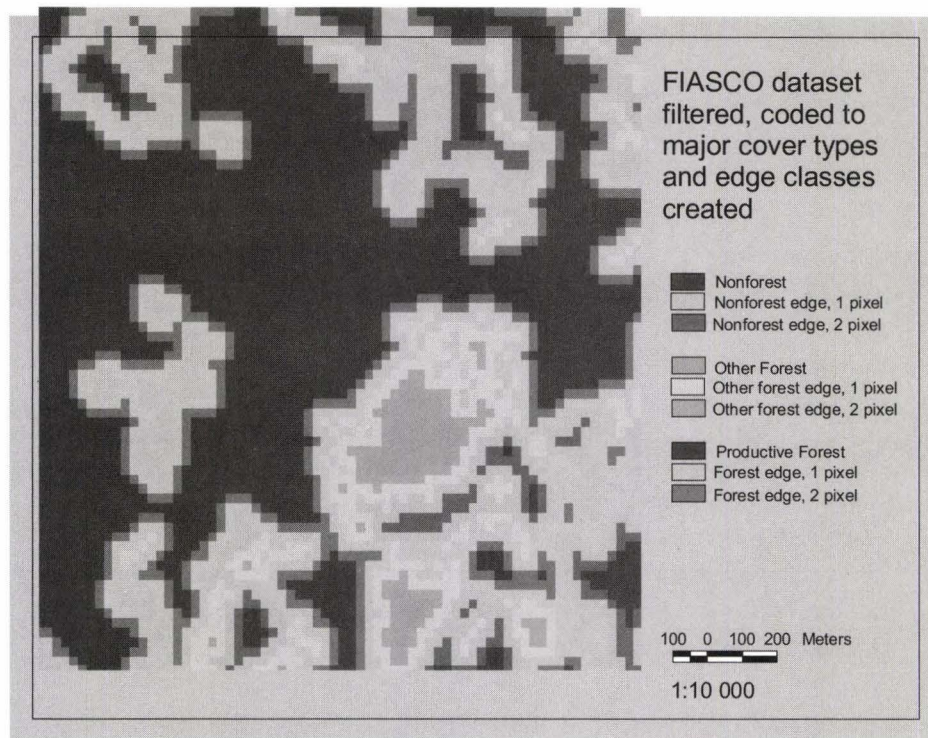


Figure 4.—Sample from FIASCO-TM GIS layer after 2-pixel-wide edge classes around forest, other forest, and nonforest classes are generated.

We tested a FIASCO-TM classification using a 20-percent sample of the PI points clustered by photo so that all points on a photo are used but only 20 percent of photos. This clustered approach is essential to reducing the photo and labor costs associated with the PI component of the FIASCO-TM approach. A post-processed version that was filtered and augmented with edge strata for forest, other forest, and nonforest (fiasco_fofnf) improved precision for estimates of timberland area and down wood.

Operational Considerations

Cost and operational issues also figure prominently in choosing a stratification system. Depending on the system, several expenses must be accounted for such as photo acquisition, photo setup and interpretation, Landsat image or GIS product acquisition and processing, and geoprocessing. Time requirements and costs were estimated based on recent PI projects and expenses incurred for this analysis, converted to a per million acres basis, and expanded to generate estimates for states in the PNW region for which a decision on Phase 1 is imminent.

RESULTS

Timberland Area

Only the PI-based stratifications were successful in achieving an error per million acres rate below the 3-percent goal specified in the Forest Service Handbook (USDA Forest Service 1967) as the most important benchmark (table 2). The best precision obtained from a semi-automated stratification system for timberland area was CALVEG with edge classes. Two of the three semi-automated stratification systems achieved substantial to excellent design effects, and one was just below substantial.

Total Volume on Timberland

The remarkable reduction in sampling error achieved for volume by substituting "optimal PI" for "production PI" suggests that considerable volume variation cannot be explained by broad forest type alone. There is very little difference in precision between the production PI and the semi-automated stratification systems, and the statistical efficiency of stratification for volume estimation is moderate at best (table 3).

Table 2.—Timberland area in the North Coast Survey Unit based on the best stratification from each data set

Method	Standard error	Timberland area	Sampling error per million acres	Design effect
	Acres	Acres	Percent	Percent
Production PI	49,852	2,924,100	2.92	30
Optimal PI	50,573	2,911,300	2.96	31
CALVEG Edge	58,599	2,854,800	3.47	41
NLCD fofnf	63,002	2,911,700	3.69	48
FIASCO fofnf	69,696	2,809,200	4.16	58
Random Sample	69,696	2,847,300	5.42	100

Table 3.—Total volume on timberland in the North Coast Survey Unit based on the best stratification from each data set

Method	Standard error	Timber volume	Sampling error per billion cu ft	Design effect
	Thousand cu ft	Thousand cu ft	Percent	Percent
Optimal PI	417,300	10,490,000	12.88	58
Production PI	464,730	10,618,000	14.26	72
CALVEG FLS	470,970	10,297,000	14.68	73
NLCD fofnf	474,250	10,410,000	14.70	74
FIASCO fofnf	465,940	10,050,000	14.70	72
Random Sample	550,100	10,245,000	17.19	100

Total Volume of Down Wood

Down wood, down logs, and branches with diameter ≥ 5 inches are important habitat components for a number of wildlife species and may be good indicators of biodiversity, but there is no precision standard for this attribute in the FS inventory system. None of the stratification systems improve the estimates of DW very much; the design effect is minimal at best (table 4). However, sampling error per billion cubic feet of DW is not much higher than it is for standing volume, so even without stratification, precision would likely be acceptable for most applications.

Operational Considerations

Costs per million acres range from \$854 for NLCD to \$82,218 for CALVEG in areas (i.e., outside of California) where that classification layer does not yet exist (table 5). Except for CALVEG outside California, all of the methods

tested would be far less expensive than PI. For methods implemented across all of California, Oregon, and Washington, the cost of stratification ranges from \$113,000 (for NLCD) to nearly \$6 million for CALVEG (table 6).

DISCUSSION

No semi-automated approach tested resulted in more precise estimates of timberland area or timber volume than can be achieved by using PI. The tradeoff curve between precision and cost (fig. 5) suggests that substantial cost savings can be achieved by transitioning to a semi-automated approach, with only modest reductions in precision. It was also shown that volume precision targets cannot be achieved using any stratification approach tested. One potential ancillary benefit not included in this analysis is the value of the forest land strata maps derived from a stratification approach like FIASCO-TM. Such GIS layers could prove useful as a spatial component in other forest research projects, particularly those involving interpolation of FIA plot attributes to the larger landscape.

Table 4.—Total volume of down wood in the North Coast Survey Unit based on the best stratification from each data set

Method	Standard error	Timber volume	Sampling error per billion cu ft	Design effect
	<i>Thousand cu ft</i>	<i>Thousand cu ft</i>	<i>Percent</i>	<i>Percent</i>
Production PI	347,630	5,692,500	14.57	78
FIASCO fofnf	367,330	5,386,000	15.83	87
CALVEG density	369,410	5,392,200	15.91	88
NLCD fnf	376,670	5,525,300	16.02	92
Random Sample	393,510	5,393,400	16.94	100

Table 5.—Estimated costs for each stratification approach on a per million acre basis

Component	Traditional PI	FIASCO-TM	NLCD	CALVEG CA	CALVEG outside CA
	<i>Cost (\$) per million acres</i>				
Photo acquisition	1,945	778			
Photo setup	14,140	5,998			
Photo interpretation	2,203	441			
Landsat scenes		36	0	0	0
GIS layer preparation		251	251	251	251
Filter and edge		503	503	1,715	1,715
Administration etc.		251	101	251	251
CALVEG creation					80,000
Total	18,288	8,259	854	2,218	82,218

Table 6.—Estimated costs for each stratification approach, by State

State	Traditional PI	FIASCO-TM	NLCD	CALVEG
	<i>Cost (thousands of \$) for entire states</i>			
California	1,116	504	52	135
Oregon	720	325	34	3,236
Washington	582	263	27	2,618
Total	2,418	1,092	113	5,989

If money is the principal concern, NLCD is very attractive for the precision achievable relative to acquisition and processing cost. However, NLCD is a pre-classified product, so FIA staff cannot fine-tune the class definitions or the number of classes that are used to describe forested areas, for example. In this regard, FIASCO-TM offers more flexibility and opportunities to tune the training information and class

definitions to match any particular or current needs. By selecting the FIASCO-TM method, the FIA program would escape dependence on update cycles and priorities of the other agencies and would be able to directly design the information included in the resulting vegetation map.

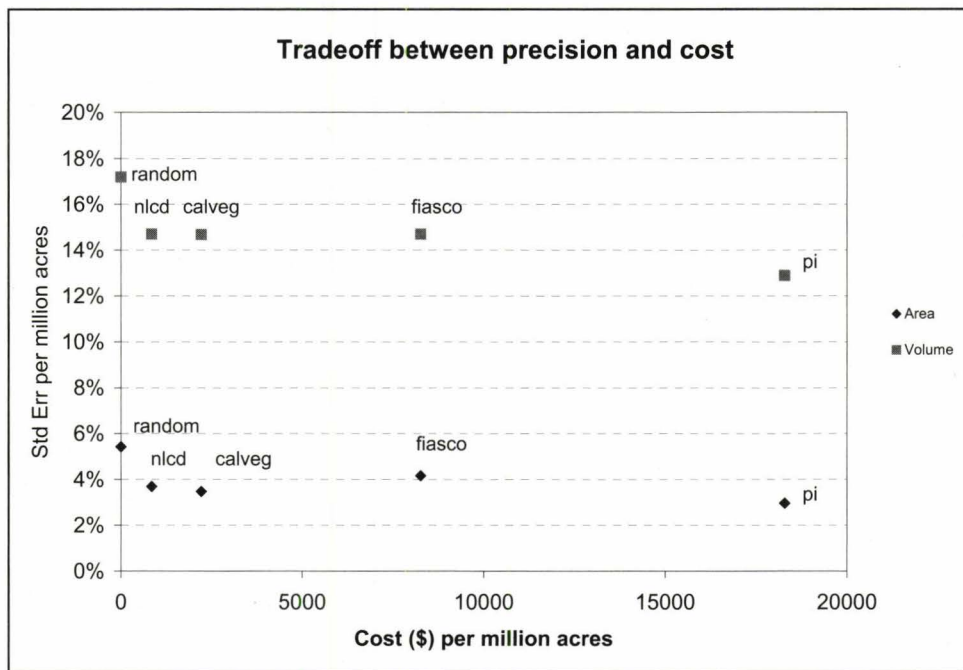


Figure 5.—Precision and estimated cost for random sample, convetional PI, and three semi-automated approaches to stratification.

Forest types vary widely in California's North Coast Survey Unit, ranging from low elevation redwood forests to alpine forest types and chaparral. However, the survey unit contains almost no sparse or transitional forest such as can be found in abundance on the east side of the Cascade Mountains. Such areas have extensive intermixing of types, potentially generating considerable confusion in stratification. Further research is needed to assess the performance of these alternatives on sparse forests. It is conceivable that different stratification systems may be needed in different parts of the PNW region. One possibility, not directly tested in this study, is to use digital elevation data to separate vegetation zones on the mountain slopes and combine this information with NLCD data. While CALVEG inherently contained some elements of this approach, there may well be opportunities to optimize for this application.

The general conclusion of this work is that Phase 1 stratifications based on digital remote sensing data can lead to precision nearly comparable to that achieved via conventional PI, and at a cost, in most cases, that is significantly lower. For non-timber attributes, stratification may provide additional precision in some cases, and the precision obtained from remote sensing stratifications for down wood abundance was essentially the same as from PI. Ultimately, the ways in which this kind of large-scale forest

inventory data are used will determine the importance of attaining accuracy standards that were set for timber attributes 35 years ago.

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STRATIFIED ESTIMATES OF FOREST AREA USING THE k-NEAREST NEIGHBORS TECHNIQUE AND SATELLITE IMAGERY

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ABSTRACT.—For two study areas in Minnesota, stratified estimation using Landsat Thematic Mapper satellite imagery as the basis for stratification was used to estimate forest area. Measurements of forest inventory plots obtained for a 12-month period in 1998 and 1999 were used as the source of data for within-strata estimates. These measurements further served as calibration data for a k-Nearest Neighbors technique that was used to predict forest land proportion for image pixels. The continuum of forest land proportion predictions were separated into strata to facilitate stratified estimation. The variances of the stratified forest area estimates were smaller than variances based on simple random estimates by factors as great as 5, and when including all plots over a 5-year plot measurement cycle, the forest area precision estimates may be expected to satisfy national standards.

The five regional Forest Inventory and Analysis (FIA) programs of the Forest Service, U.S. Department of Agriculture, report estimates of forest land area for their respective regions every 5 years. Each estimate is obtained as the product of total area inventoried and the mean over a systematic array of field plots of the proportion of each plot in FIA-defined forest land. The FIA definition of forest land includes commercial timberland, some pastured land with trees, forest plantations, unproductive forested land, and reserved, non-commercial forested land. In addition, forest land must satisfy minimum stocking levels, a 0.405-ha (1-acre) minimum area, and a minimum continuous canopy width of 36.58 m (120 ft). It therefore excludes lands such as wooded strips, idle farmland with trees, and narrow wind-breaks. A combination of budgetary constraints and natural variability among plots prohibits sample sizes sufficient to satisfy national FIA precision standards for forest land estimates unless the estimation process is enhanced using ancillary data.

One approach to enhancing the estimation process is to use stratified estimation with classified satellite imagery as the

basis for the stratification. With this approach, image pixels for the area of interest are classified with respect to predictions of land cover attributes into homogeneous classes, and the classes are then used as strata in the stratified analyses. Strata weights are the proportions of pixels in strata, and plots are assigned to strata on the basis of the strata assignment of their associated pixels. If the stratification is accomplished prior to sampling and the within-strata variances of the inventory variables are well-estimated, then maximum precision may be achieved by designing within-strata sampling intensities to be proportional to within-strata variances. However, even when the within-strata sampling intensities are independent of the stratification, stratified estimation may still yield increases in precision.

The timeliness of FIA estimates is enhanced when cycles for obtaining and classifying imagery are comparable to the 5-, 7-, or 10-year plot measurement cycles, depending on region. On average, a regional FIA program on a 5-year plot measurement cycle will need to classify approximately 125 TM images over the cycle. In addition, sufficient training data to guide the classifications must be obtained in close temporal proximity to the imagery dates. These are not insignificant tasks, and investigation of efficient means of obtaining training data and processing images are worthwhile FIA endeavors. The objective of this study is to investigate the utility of the k-Nearest Neighbors technique for processing TM imagery to be used as the basis for enhancing forest area estimates through stratification.

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DATA

Study Areas

The study was conducted in two areas, designated St. Louis and St. Cloud (fig. 1). The St. Louis study area encompasses most of St. Louis County, Minnesota; includes approximately 2.1 million hectares of which approximately 75 percent is forest land; and is dominated by Aspen-Birch and Spruce-Fir associations. The St. Cloud study area contains the St. Cloud, Minnesota, urban area; includes approximately 3.3 million hectares of which approximately 20 percent is forest land; and is characterized by prairie agriculture and a diverse mixture of forest lands including both coniferous and deciduous species.

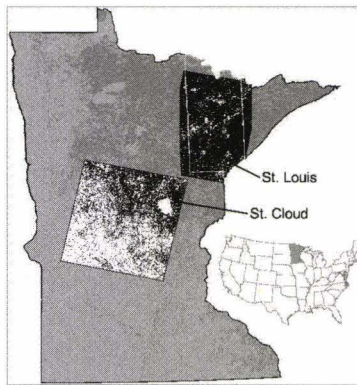


Figure 1.—Minnesota study areas.

Satellite Imagery

The St. Louis study area is covered by the Landsat TM Path 27, Row 27 scene and includes all of St. Louis County except the northern portion. For this scene, Landsat-7 ETM+ images were obtained for two seasons: autumn (5 November 1999) and summer (31 May 2000). The St. Cloud study area is covered by the Landsat TM Path 28, Row 28 scene. For this scene, Landsat-7 ETM+ images were obtained for three seasons: summer (23 July 1999), autumn (27 October 1999), and spring (3 March 2000). The following attributes pertain to all five images: (1) 30 x 30 m pixels from bands 1-5 and band 7; (2) absolute radiance units scaled to 8 bits; (3) processing to level 1G (processing level 08; radiometrically and geometrically corrected using satellite model and platform/ephemeris information); and (4) geo-referencing to Albers Equal Area projection, NAD83. In addition, for the St. Louis study area, the November image was rectified using 40 ground control points with resulting root mean square error of 12.1 m. The

May image was registered to the November image using 26 ground control points and resampled using first-order polynomial and nearest neighbor techniques with resulting root mean square error of 31.9 m. For the St. Cloud study area, all three images were rectified using ground control points and digital elevation model terrain correction (processing level 10) and resampled using cubic convolution with resulting root mean square error less than 8.5 m. Finally, bands are distinguished using an alphanumeric character representing the first letter of the month of the image and a numeric character designating the band. The context of band references indicates whether they refer to St. Louis or St. Cloud images.

FIA PLOT DATA

Under the FIA program's annual inventory system (McRoberts 1999), field plots are established in permanent locations using a systematic sampling design. In each State, a fixed proportion of plots are measured annually; plots measured in a single Federal fiscal year (e.g., FY-1999: 1 October 1998 to 30 September 1999) make up a single panel of plots with panels selected for annual measurement on a rotating basis. In aggregate, over a complete measurement cycle, a plot represents 2,403 ha (5,937 acres). In general, locations of forested or previously forested plots are determined using global position system receivers, while locations of non-forested plots are determined using digitization methods.

Each field plot consists of four 7.31-m- (24-ft) radius circular subplots. The subplots are configured as a central subplot and three peripheral subplots with centers located at 36.58 m (120 ft) and azimuths of 0°, 120°, and 240° from the center of the central subplot. Among the observations field crews obtain are the proportions of subplot areas that satisfy specific ground land use conditions. Subplot-level estimates of forest land proportion are obtained by aggregating these ground land use conditions consistent with the FIA definition of forest land, and plot-level estimates are obtained as means over the four subplots.

For both study areas, measurements for the FY-1999 panel of inventory plots were available. For the St. Louis study area, measurements for 133 plots or 532 subplots were used of which 387 subplots were completely forested, 7 subplots were partially forested, and 138 subplots were non-forested. For the St. Cloud study area, measurements for 268 plots or 1,072 subplots were used of which 226 subplots were completely forested, 13

subplots were partially forested, and 833 subplots were non-forested.

K-NEAREST NEIGHBORS TECHNIQUE

The k-Nearest Neighbors (k-NN) technique is a non-parametric approach to predicting values of point variables on the basis of similarity in a covariate space between the point and other points with observed values of the variables. For this application, consider a TM image pixel to be a point, let Y denote a ground attribute (e.g., forest land proportion, cumulative volume of individual trees, tree density) of the pixel, and let X denote its vector of TM spectral values. Let U denote the finite set of image pixels, and let U be indexed by $i=1, \dots, N$; let S denote the subset of pixels of U that correspond to FIA subplots (i.e., the subset of pixels of U for which surrogates for the pixel-level observations of the ground attribute are available), and let S be indexed by $j=1, \dots, n$. The objective is to obtain a prediction of the ground attribute for each pixel. With the k-NN technique, predictions, $\hat{Y}_i$, for Y_i are obtained in two steps:

1. for each $(Y_i, X_i) \in U$ re-order $\{(Y_j, X_j) | Y_j \in S\}$ with respect to increasing distance, d_{ij} , between X_i and each X_j , excluding Y_i from the ordering if $(Y_i, X_i) \in S$, also; denote the resulting ordering $\{(Y_{ij}, X_{ij})\}$;

2. for each $Y_i \in U$,

$$\hat{Y}_i = \left(\sum_{j=1}^k w_{ij} \right)^{-1} \left(\sum_{j=1}^k w_{ij} Y_{ij} \right) \quad (1)$$

where k is a predetermined constant, $1 \leq k < n$, and $\{w_{ij}\}$ are point weights to be selected.

The quality of predictions may be assessed using $\{Y_j | (Y_j, X_j) \in S\}$, the root mean square error (RMSE) criterion,

$$RMS_e = \sqrt{\left(Y_j - \hat{Y}_j \right)^2} \quad (2)$$

and the leaving-one-out method. With the leaving-one-out method, a k-NN prediction, $\hat{Y}_j$, is sequentially obtained for each Y_j , but with the provision that Y_j itself cannot be included in the mean forming its own k-NN prediction. In addition, to avoid

issues related to the expected high correlation expected among attributes for subplots of the same plot, for this study the prediction for a subplot was constrained against including an observation for any of the other three subplots of the same plot. By comparing the observations, $\{Y_j | (Y_j, X_j) \in S\}$, and corresponding predictions, $\{\hat{Y}_j | (Y_j, X_j) \in S\}$, with respect to the RMS_e criterion, the quality of predictions may be evaluated.

Before implementation, the k-NN technique must be calibrated. First, the particular spectral bands used to calculate the distances, d_{ij} , between X_i and each element of the set, $\{X_j | (Y_j, X_j) \in S\}$, must be selected. Let Z denote the subset of X consisting of the selected bands, and let the elements of Z be indexed by $m=1, \dots, M$. Second, a distance metric, d , must be selected; among the alternatives are weighted Euclidean distance,

$$d_{ij} = \left[\sum_{m=1}^M v_m (Z_{im} - Z_{jm})^2 \right]^{-1} \quad (3)$$

where $\{v_m\}$ are variable weights, and Mahalanobis distance,

$$d_{ij} = \left(Z'_i - Z'_j \right)' V^{-1} \left(Z'_i - Z'_j \right) \quad (4)$$

where V is the covariance matrix for $Z \subset X_j$. If weighted Euclidean distance is selected, then the variable weights $\{v_m\}$ for (3) must also be selected. Third, the value of k , the number of nearest neighbors to be included in the calculation of predictions (1), must be selected. Finally, the point weights, $\{w_{ij}\}$, for (1) must be selected; common alternatives include constant weighting for which $w_{ij}=1$, inverse distance weighting for which $w_{ij}=d_{ij}^{-1}$, and inverse distance squared weighting for which $w_{ij}=d_{ij}^{-2}$.

The k-NN analyses were conducted at the subplot-pixel level, because a plot-level approach would require calibration using means of inventory observations over the four subplots and either means of TM spectral values over the four pixels corresponding to the four subplots or means over a block of pixels covering the plot. Predictions for image pixels must likewise then be based on the mean over four pixels in the same configuration as the four pixels corresponding to the four subplots or the mean over a block of pixels of the same size and configuration as the block covering the plot. For this study, subplot-pixel level analyses entail a simpler approach without sacrificing statistical validity. Thus, each subplot was associated with the TM pixel with center closest to the subplot center.

ANALYSES

For this application, the selected k -value was $k=k_{opt}$, the k -value that minimizes RMS_e . For each study area, k_{opt} was determined for each combination of spectral bands by comparing values of RMS_e obtained with constant variable and constant point weighting. For each study area, the five spectral band combinations with the smallest RMS_e without regard to the number of bands, were selected for further evaluation.

Creating Strata

For each of the five best spectral band combinations for each study area, forest land proportion was predicted for each image pixel using the k -NN technique with the k_{opt} determined for that band combination. From the resulting continuum of predictions for each image, four optimal strata were selected by considering all possible divisions of the continuum into four classes under three constraints: first, the lower bound of the first stratum was always 0.00, and the upper bound of the fourth stratum was always 1.00; second, the minimum stratum width was 0.05; and third, at least five plots were required to be assigned to each stratum. Stratifications were limited to four strata, because the preponderance of observed forest land proportions were either 0.00 or 1.00. Each pixel was assigned to a stratum based on its forest land proportion prediction, and strata weights were calculated as the proportions of pixels assigned to strata. To avoid the mathematical complexity necessary to accommodate the spatial correlation among the four subplot observations, FIA assigns plots rather than subplots to strata for stratified analyses. Each plot was assigned to a stratum on the basis of the stratum assignment of the pixel corresponding to the center of the center subplot. Plots were stratified using predictions of forest land proportion for their corresponding pixels rather than observations so that the assignment of plots to strata would be consistent with the calculation of strata weights. Stratifications were evaluated with respect to relative efficiency, RE, the ratio of the variance of the mean obtained using simple random analyses and the variance obtained using stratified analyses.

Stratified Estimation

Stratified estimates of mean forest land proportion, $\bar{Y}$, and estimated variance, $\hat{Var}(\bar{Y})$, were calculated using standard methods (Cochran 1977)

$$\bar{Y} = \sum_{j=1}^J w_j \bar{Y}_j \quad (5)$$

and

$$\hat{Var}(\bar{Y}) = \sum_{j=1}^J w_j^2 \frac{\hat{\sigma}_j^2}{n_j} \quad (6)$$

where $j=1, \dots, J$ denotes stratum; w_j is the weight for the j^{th} stratum; $\bar{Y}_j$ denotes the mean forest land proportion for plots assigned to the j^{th} stratum; n_j is the number of plots assigned to the j^{th} stratum; and $\hat{\sigma}_j^2$ is the within-stratum variance for the j^{th} stratum calculated as,

$$\hat{\sigma}_j^2 = (n_j - 1)^{-1} \sum_{i=1}^{n_j} (Y_{ij} - \bar{Y}_j)^2 \quad (7)$$

where Y_{ij} is the forest land proportion observed by the field crew for the i^{th} plot in the j^{th} stratum. Variance estimates obtained using (6) ignore the slight effects due to finite population correction factors and to variable rather than fixed numbers of plots per stratum.

The FIA program reports precision estimates as coefficients of variation scaled to compensate for varying sample sizes using as a reference standard the sample size corresponding to 404,694 ha (1 million acres) (USDA FS 1970). For forest area estimate, $\hat{FA} = A \bar{Y}$, the scaled precision estimate, denoted PREC, is defined for this study as

$$PREC = \left[\frac{\hat{Var}(\hat{FA})}{\hat{FA}} \right]^{\frac{1}{2}} \left[\frac{\hat{FA}}{404,694} \right]^{\frac{1}{2}} = \left[\frac{\hat{Var}(\hat{FA})}{404,694(A\bar{Y})} \right]^{\frac{1}{2}} \quad (8)$$

where $\bar{Y}$ is again mean forest area proportion per plot, and A is total area inventoried in ha. Two values of PREC are reported, the value obtained from (8) which corresponds to the sample size resulting from a single panel of plot measurements and the value obtained from (8) divided by the square root of 5 which corresponds to the value expected with the sample size resulting from all five panels of plots. The national FIA precision standard is $PRE \leq 0.03$.

RESULTS

The general results are that the k -NN algorithm was very simple to implement, straightforward to calibrate, and required no user intervention after initiation. The k -NN predictions captured

much of the forest/nonforest detail and provided an excellent basis for stratifications. When compared to variances of forest area estimates obtained using simple random estimation, the variances obtained using stratified estimation were smaller by factors as great as 5. Specific results follow.

Both similarities and differences were noted among calibrations for the five best band combinations and the resulting stratified estimates (table 1). The similarities:

1. the means for the five best band combinations were comparable within study areas;
2. values of RMS_e , SE, RE, and PREC were generally of the same order of magnitude both within and between study areas;
3. the bands selected for the five best band combinations were similar within study areas with N3, N4, and M4 selected for all five combinations for the St. Louis study area, and J3, M3, and M4 selected for all five combinations for the St. Cloud study area; bands 3 and 4 were most commonly selected, while bands from the spring 2000 images were selected for all five best band combinations for each study area;
4. for both study areas, the stratifications based on the k-NN analyses produced expected five-panel precision for forest land area estimates that satisfied the national FIA precision standards;
5. for each best band combination, multiple sets of between-strata boundaries produced similar values of RE.

The differences:

1. the ordering of the band combinations with respect to RE, or equivalently PREC, was not the same as that with respect to RMS_e , suggesting that if the optimal band combination is desired, then evaluating the five best band combinations selected with respect to RMS_e , as was done for this study, is recommended;
2. optimal between-strata boundaries for the St. Louis study area differed considerably, although as noted previously multiple sets of between-strata boundary combinations for the same band combination produced similar values of RE.

CONCLUSIONS AND DISCUSSION

Four important conclusions may be drawn from this study:

first, although the k-NN technique is conceptually easy to implement, careful attention must be paid to its calibration if optimal results are expected; second, stratifications derived from TM imagery reduced variances of forest area estimates by factors as great as 5 for both a heavily forested area and a sparsely forested area; third, the stratifications may be expected to produce forest land area estimates that satisfy national FIA precision standards for sample sizes corresponding to five panels of measurements; and fourth, the k-NN technique is a viable alternative for processing satellite imagery that is both faster and easier to implement than traditional image classification methods.

The implications of the latter three conclusions for the FIA program are considerable. First, in the absence of stratification, sample sizes would have to be increased by factors as least as great as 5 to achieve the same level of precision as was obtained with the stratifications. The magnitude of the resulting cost saving is substantial. For the State of Minnesota, with a sampling intensity of one plot for every 2,403 ha, approximately 825 plots are field-measured annually at an FY1999 cost of approximately \$1,000 (US) per plot. Thus, the annual cost savings obtained with such stratifications is approximately \$3,300,000 (US).

Second, the effectiveness of the k-NN algorithm frees the FIA program from more costly and less timely alternatives. The speed and automation of the k-NN technique make it vastly superior to FIA's time-consuming, labor-intensive, traditional approach based on interpreting aerial photographs. A crew of four photointerpreters, working full-time, could be expected to complete the photointerpretation and stratification task for the State of Minnesota in 2-3 years. Alternatively, processing of the approximately 15 TM images necessary for full coverage of the State of Minnesota could be expected to be accomplished using the k-NN technique in 2-3 weeks by a single computer technician.

Table 1.—Mean forest land proportion estimates

Rank ^a	RMS _e	Bands					k	Optimal between-strata boundaries			Mean	SE ^b	RE ^c	PREC ^d	
														1 panel	5 panels
St. Louis study area															
1	0.2652	N3	N4	M4			9	0.20	0.75	0.95	0.7547	0.0175	4.4836	0.0455	0.0203
2	0.2687	N1	N3	N4	M4		7	0.10	0.70	0.80	0.7493	0.0188	3.8864	0.0490	0.0219
3	0.2690	N2	N3	N4	M4		9	0.20	0.50	0.75	0.7593	0.0177	4.3943	0.0459	0.0205
4	0.2690	N3	N4	M1	M4		11	0.55	0.60	0.90	0.7845	0.0157	5.5912	0.0400	0.0179
5	0.2693	N2	N3	N4	M1	M4	13	0.50	0.70	0.95	0.7681	0.0182	4.1655	0.0469	0.0210
St. Cloud study area															
1	0.2392	J2	J3	M3	M4		21	0.10	0.40	0.75	0.2312	0.0107	4.9189	0.0635	0.0285
2	0.2399	J2	J3	M1	M3	M4	29	0.15	0.45	0.70	0.2313	0.0107	4.9587	0.0635	0.0284
3	0.2406	J2	J3	M2	M3	M4	33	0.20	0.40	0.75	0.2346	0.0109	4.7837	0.0643	0.0287
4	0.2420	J3	M3	M4			23	0.25	0.45	0.60	0.2367	0.0103	5.3847	0.0605	0.0270
5	0.2423	J3	M1	M3	M4		23	0.25	0.45	0.65	0.2398	0.0105	5.1238	0.0612	0.0274

^a Rank based on RMS_e.

^b Standard error of mean, calculated as the square root of the variance of the mean (6).

^c Relative efficiency of the stratification, calculated as the ratio of the variance of the mean assuming simple random sampling and the variance of the mean based on stratified analyses (6).

^d FIA precision calculated from (8).

Finally, better future results may be expected with the k-NN technique. Fine-tuning the calibration of the k-NN technique by including point- and variable-weighting will increase the accuracy of classifications. Also, five panels of plot measurements will increase the density of observations in spectral space, allow each k-NN prediction to be based on subplot-pixel observations in closer spectral proximity, and, therefore, increase the accuracy of individual pixel predictions.

In conclusion, the k-NN technique is a viable and efficient method for processing TM images to obtain predictions of forest area proportion, and stratifications derived from these predictions produce forest area estimates that may be expected to satisfy national FIA precision standards.

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PROGRESS IN ADAPTING k-NN METHODS FOR FOREST MAPPING AND ESTIMATION USING THE NEW ANNUAL FOREST INVENTORY AND ANALYSIS DATA

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ABSTRACT.—The k-nearest neighbor (k-NN) method has been undergoing development and testing for applications with USDA Forest Service Forest Inventory and Analysis (FIA) data in Minnesota since 1997. Research began using the 1987-1990 FIA inventory of the state, the then standard 10-point cluster plots, and Landsat TM imagery. In the past year, research has moved to examine potentials for improving cover type and volume mapping and estimation with the new annual FIA data, notably the new four-subplot cluster plot, and Landsat ETM+. Major findings to date point to the difficulty of choosing the number of neighbors (k). A value of k between 1 and 3 seems appropriate for mapping. A larger number of neighbors reduces the overall estimation error, but it also leads to a reduction in the producer's accuracy. Additionally, using multiple image dates for an area typically improves results considerably. Recent results with the new four-subplot cluster plot data show that stratification of the data into upland/lowland strata, use of thermal bands, and a plot location optimization all improve mapping and estimation results. Finally, segmentation algorithms show potential for improving mapping and the k-NN estimation process. A C-language program package for applying the k-NN method to forest inventory has also been developed.

BACKGROUND

A non-parametric method for estimation of forest variables has been used operationally in the Finnish National Forest Inventory since the early 1990s (Muinonen and Tokola 1990; Tokola and others 1996; Tomppo 1990, 1993). This method estimates forest variables by calculating a weighted average of measurements from a number of field sample plots. Weights are assigned according to the distance in spectral space, defined by the satellite image bands, between the pixel under classification and field sample plots. The k-nearest neighbor (k-NN) method can estimate multiple forest variables simultaneously and is a simple but powerful way to extend a wide range of field data to landscapes. The method can also preserve the covariance structure of forest variables and thus

produce maps that appear very realistic in terms of their spatial pattern.

Adapting the Finnish-developed k-NN technique to the FIA four-subplot cluster plot data and to the complex structure of Lake States forests has been a main study objective. The research poses significant challenges, but if these can be met, the combination of multispectral satellite imagery and existing field plot-based inventory data can be used to create detailed maps of volume, basal area, cover type, and annual change on an objective basis, at low cost, and with useful precision and a high degree of automation.

Additionally, the k-NN method can produce very local estimates with much improved precision. With k-NN, the information contained in field samples (FIA plots) is propagated across the entire population under the assumption that similar forest conditions exist across the satellite imagery and the measured spectral-radiometric-temporal responses of pixels in the imagery are dependent on the forest conditions.

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PREVIOUS RESULTS WITH THE OLD FIA DESIGN

The adaptation of the k-NN method for the forests of Lake States began with the old FIA 10-point cluster plot design (see Franco-Lopez and others 2001). This research led to important findings on the behavior of the k-NN method in complex mixed species forests. The following list includes the most important results.

1. Larger numbers of neighbors (k) reduce the overall estimation error, but also reduce the producer's accuracy.
2. Using multiple (up to three) satellite images from different dates significantly improves results.
3. For the measure of distance between pixels in spectral space, the Euclidean distance proved superior to the Mahalanobis distance.
4. Filtering had little effect, e.g., pixel-based results were judged equivalent or better than using a 3 x 3 filter.
5. The best estimation accuracies at the pixel level with the old plot design were typically 60 to 85 percent root mean square error (RMSE) for volume and 45 to 55 percent correctly classified into the FIA cover type classification (14 forest cover types, USDA 2000).

STUDY AREA AND MATERIALS FOR THE RECENT STUDIES WITH THE NEW FIA DESIGN

Most studies have been conducted in northeastern Minnesota, specifically the FIA Aspen-Birch Survey Unit (unit 1). The area is approximately 29,748 km². However, the wall-to-wall extension of volume, basal area, and cover type has been developed for unit 1 and parts of unit 2 (Northern Pine Survey Unit).

Field Data

The new FIA four-subplot cluster plot (USDA 2000) data were used in the k-NN estimation. So far, however, only the first-year (1999) panel or set of plots has been available. The second-year panel (2000) will be added to the database when it arrives. The 1999 panel provided 180 forested plots in the study area, which led to 720 subplots, nearly all of which were forested. Mean volume for these plots was approximately 62 m³/ha (890 ft³/acre).

Image and Digital Map Data

The predominant imagery used was Landsat 7 ETM+ satellite images; when these were not available because of clouds, Landsat 5 TM images were used. Typically, two to four image dates were available for each scene used in the study. The satellite image database preprocessed for k-NN classification covered FIA unit 1 and parts of units 2 and 3 (Central Hardwoods Survey Unit) in Minnesota. The database included 13 satellite images: 8 Landsat 7 ETM+ images and 5 Landsat 5 TM images.

Digital map data are used to remove nonforest land use classes from the estimation and mapping process and to improve the accuracy of estimates (upland/lowland stratification). A mid-1990s Minnesota land use/land cover map with 30-m pixel size was used for this purpose (<http://lucy.lmic.state.mn.us>).

C-Program Package

A C-language program package for k-NN method estimation has been developed and tested. The package includes all the necessary tools for estimation of both categorical and continuous variables using Landsat data and the new FIA four-subplot cluster plot data. Estimation software includes a cross-validation program for error estimation (for both continuous and class variables), an optimization program to find the best weights for different channels in satellite images, and a mapmaker for implementing the actual k-NN classification. The programs also include features that allow geographic and other constraints in neighbor selection, band selection, optimal band weighting, and use of different mask files. These features are useful for both research and operational k-NN estimation. A manual for using the programs for k-NN-based estimation protocols has also been published (Haapanen and others, in prep. (c)), and it is now available on the Web at: <http://www.cnr.umn.edu/FR/publications/staffpapers/index.html>.

A set of programs for segmentation (polygon development) has also been developed. At the moment a preliminary program is ready (Haapanen and others, in prep. (c)). This software is modeled after approaches used in Finland. The segmentation may be used before or after the k-NN classification, e.g., to reduce the noise and make the stand borders clearer. There are some obvious application interests for forest cover type mapping, and we are communicating with cooperators on such potentials. However, the approach needs more exploration before it is clear just how it may aid k-NN applications.

METHODS

K-nearest Neighbor Method

For estimation with Euclidean distances, consider the spectral distance $d_{p_i,p}$ computed in the feature space from the pixel to be estimated p to each pixel p_i for which the ground measurement or class is known. For each pixel p , take the k -nearest field plot pixels (in the feature space) and denote the distances from the pixel p to the nearest field plot pixels by $d_{p_1,p}, \dots, d_{p_k,p}$ ($d_{p_1,p} \leq \dots \leq d_{p_k,p}$). The estimate of the variable value for the pixel p is then expressed as a function of the k closest units, with $k \sim 1-10$, and each such unit is weighted according to a distance function in the feature space. A commonly used function for weighting distances is

$$w_{(p_i)p} = \frac{1}{d_{(p_i)p}^t} / \sum_{j=1}^k \frac{1}{d_{(p_j)p}^t} \quad (1)$$

with $t=2$.

The estimate of the variable m for pixel p is then

$$\hat{m}_p = \sum_{i=1}^k w_{(p_i)p} \cdot m_{(p_i)} , \quad (2)$$

where $m_{(p_i)}$, $i=1, \dots, k$, is the value of the variable m in sample plot i corresponding to the pixel $p_{(i)}$ which is the i th closest pixel (of "known" pixels) in the spectral space to the pixel p . Additionally, for estimation of class variables such as forest cover type, the modal cover type of the k nearest neighbors serves as the estimator. Readers may note that the overall method is a form of post-stratification.

Selection of Parameters

To obtain reliable estimates with the k -NN estimation method, it is important to have a rather large field plot sample. Theoretically speaking, one seeks to have all of the forest conditions represented in the sample. Without such representation, the estimation is limited in terms of effectively propagating all of the forest conditions across the subject area or population. For Nordic forest conditions, the understanding to date is that at least 500 sample plots are needed (Nilsson 1997), and we concur on this number for Minnesota. Beyond that, the most important parameters to be selected are the distance metric, the number of nearest neighbors k , parameters related to the digital elevation model, and stratification of the image data (Katila and Tomppo 2000).

Upland/Lowland Stratification

As has been found in Finland, the spectral response of lowland differs from that of uplands. In Minnesota this may be due in part to species concentrations (e.g., black spruce on lowlands) and possibly site factors. As a consequence, we employed upland/lowland stratification to improve the accuracy of estimates.

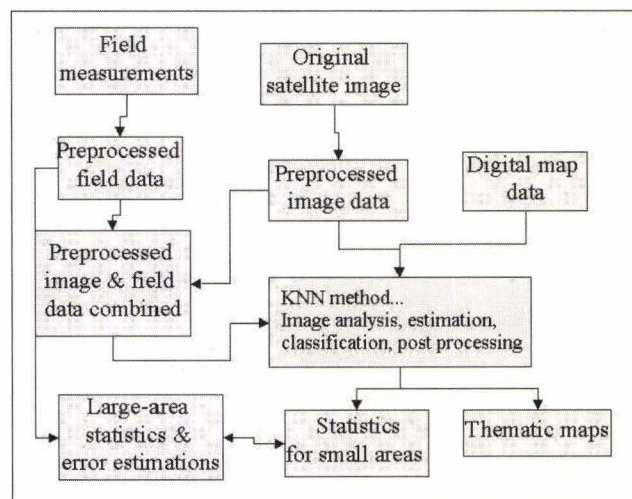


Figure 1.—Flowchart of the k -NN estimation and classification process.

The Location of Pixels

The pixel-level estimates are sensitive to field plot location and rectification errors. Errors can be mitigated to some extent by choice of the value of k . However, a high value of k shifts the estimates of the variables towards their mean values and reduces the variation. A quasi-optimization procedure for identifying the best match of pixel and field plot location has been developed, and preliminary results seem promising. The method is simplified to consider each plot and its nearby pixels, one plot at a time. This is in contrast to the approach developed by Halme and Tomppo 2001, which considers the entire inventory of plots and their locations simultaneously.

The quasi-optimization involved identifying a 3×3 pixel area around the center subplot location. The entire four-subplot cluster was then moved in the same direction, and the correlation between subplot volume and selected spectral bands was calculated. In effect, we sought the location that maximized the above correlation on the plot over the four

subplots. Also, when we calculated the correlations for a four-subplot cluster for a given test location, we moved all the subplots in tandem, i.e., given the center subplot location, and assumed the other subplots to be in their correct location relative to each other. Image dates were treated separately and allowed different optimal locations.

Finally, using the software noted above, we have been examining the potentials of segmentation approaches in conjunction with k-NN methods. The last part of the paper describes this work and plans.

RESULTS AND DISCUSSION

The FIA Four-Subplot Cluster

The four-subplot cluster plot has some interesting features when used in k-NN classification (fig. 2). Since the subplots are very close to each other, the spectral values for pixel values tend to be very similar within a cluster. In cover type classification, the entire four-subplot cluster was often of the same cover type and thus the nearest neighbors were usually found within the cluster. This result can clearly impact inventory-wide calculations and interpretation of overall accuracies in classifications.

Upland/Lowland Stratification

The upland/lowland division was made using the Minnesota land use/land cover map. As anticipated, the stratification improved the cover type accuracies for both strata (fig. 3).

Multitemporal Images

Using more than three image dates did not seem to improve the results (fig. 4). In this case the three images were March, April, and May. The fourth image added (a July date) did not improve results.

Larger Study Area Versus Multiple Dates

A comparison was made between two, three, and four image dates. The two image date data set included the study area and a portion of the adjacent Landsat scene south of the primary study area. The three and four image date data sets did not extend beyond the primary study area. Results indicated only the oak, elm-ash-cottonwood, and maple-basswood cover types benefited from an increase in number of field plots as judged by the producer's accuracy. The increase in the number of field plots with two image dates was over 45 percent for these three

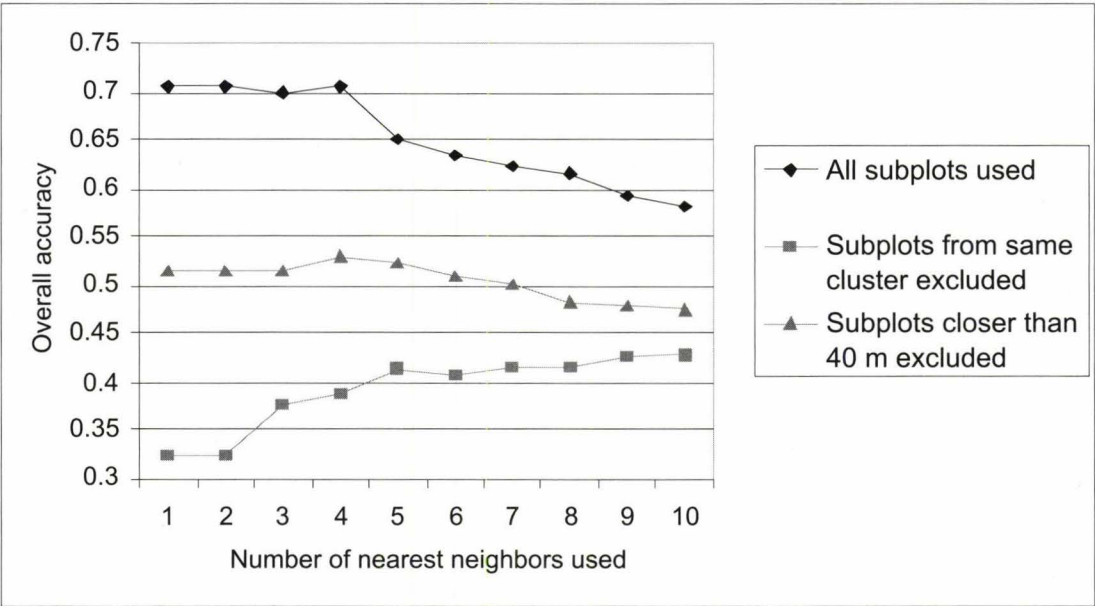


Figure 2.—Effect on overall accuracy of forest cover type estimation from limiting the inclusion of subplots.

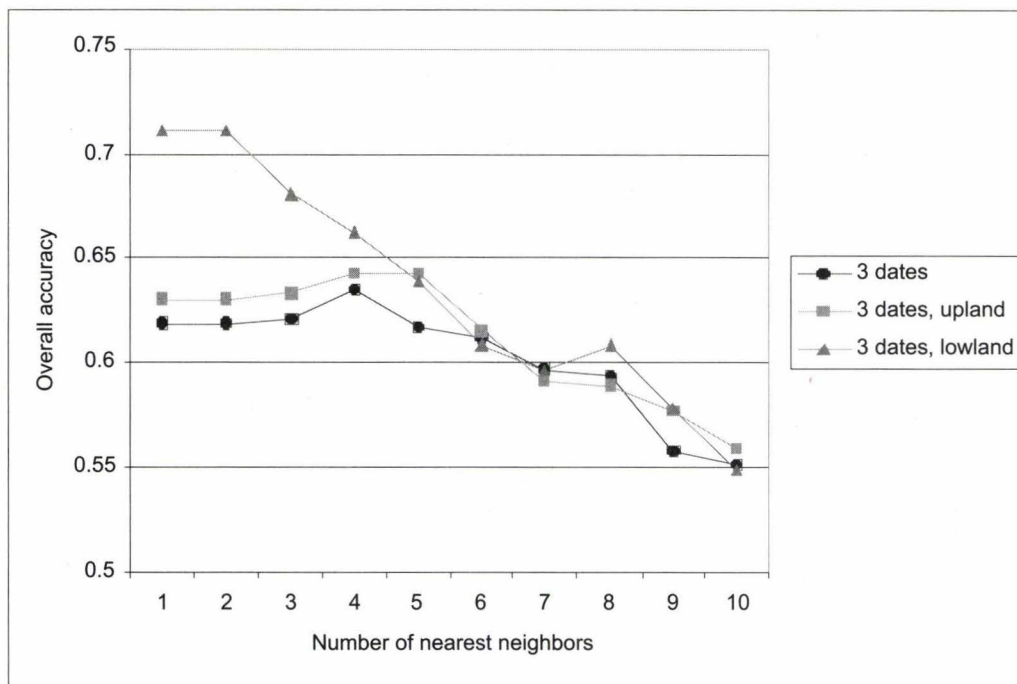


Figure 3.—Effect on overall accuracy of forest cover type estimation with stratification of field data into upland and lowland classes, northeastern Minnesota, 1999 FIA data, $n = 717$ subplots.

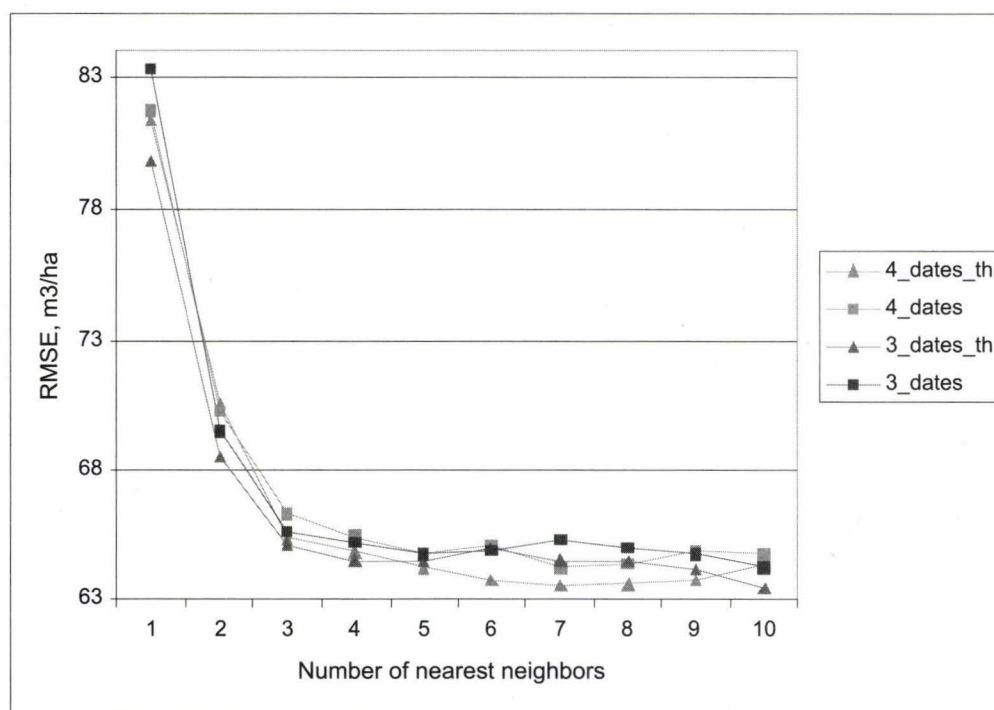


Figure 4.—RMSE for volume estimation for three and four dates of imagery (March, April, May, and July) with thermal bands, $n = 685$ subplots.

classes, and the accuracies changed as follows: oak 44 to 64 percent, elm-ash-cottonwood 47 to 52 percent, and maple-basswood 56 to 60 percent. However, the accuracies of most of the other 13 classes fell, indicating that an additional optimal image date (in this case the March image) was more important than the additional plot data available when only two dates were considered (fig. 5).

Weighting of Spectral Bands

The weighting of spectral bands improved the cover type classification accuracy from 70 to 82 percent for $k = 1$, when all subplots were included in the analysis. The volume RMSEs dropped from 80.7 to 69.4 m^3/ha with similar parameters. However, the determination of weights was not straightforward. Results for different cycles (optimizations based on different—arbitrarily chosen—starting points) show local optima, thus the approach is not without some problems.

Thermal Bands

Thermal bands were found to add important information to the classifications for forest cover type classification and to a lesser degree those for volume (fig. 6). When all subplots were included in the error estimation process, the thermal

bands improved results. The benefits for cover type classification were also evident when subplots from the same cluster (those within 70 m) as neighbors were prohibited (overall accuracy 29 percent without and 33 percent with thermal bands). In volume estimation, the results with use of thermal bands improved only for $k = 1$.

Forest/Nonforest Classification

The viability of using k -NN for FIA specified forest/nonforest classification has been tested, with preliminary results showing 86 percent accuracy. A paper describing these results is in preparation.

Plot Location Optimization

Plot location optimization was tested for both volume and cover type. The same plot locations, obtained by studying the correlation between volume and selected image bands, were used for estimating both variables. The cover type accuracies did not benefit from the location optimization, but for volume, the results were slightly better than the band optimization results described earlier. When the data were stratified into upland and lowland, the plot location optimization gave the best results for upland, but no optimization performed best on lowland. However, the differences in results for lowland were

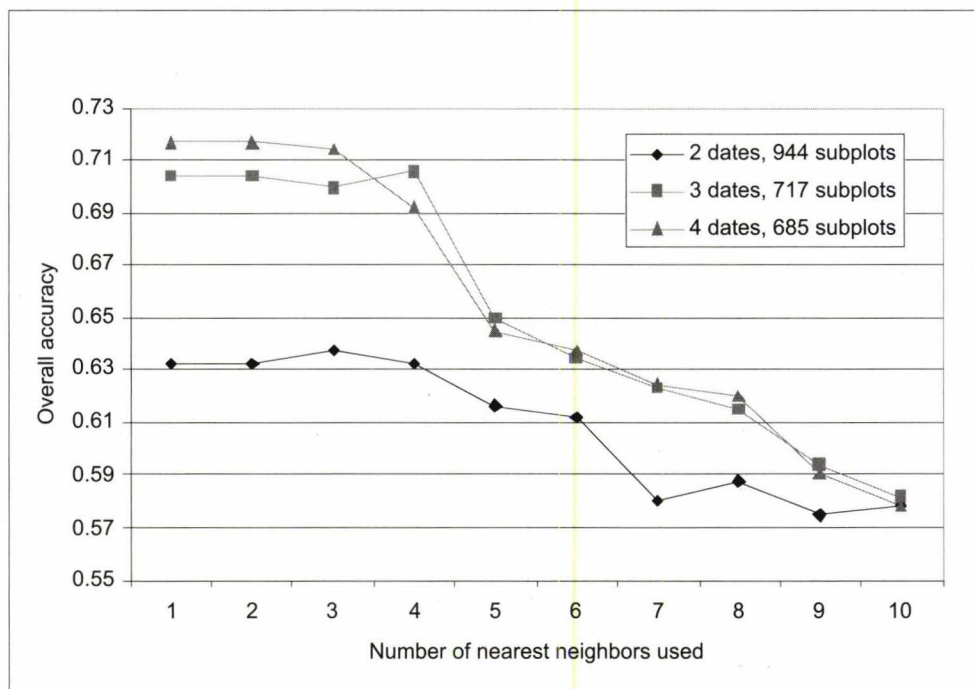


Figure 5.—Comparison of overall accuracies for forest cover type classification when two (April and May), three (March added), or four (July added) image dates are used; the number of subplots is 944, 717, and 685, respectively. Thermal bands included except for the July image (Landsat 5).

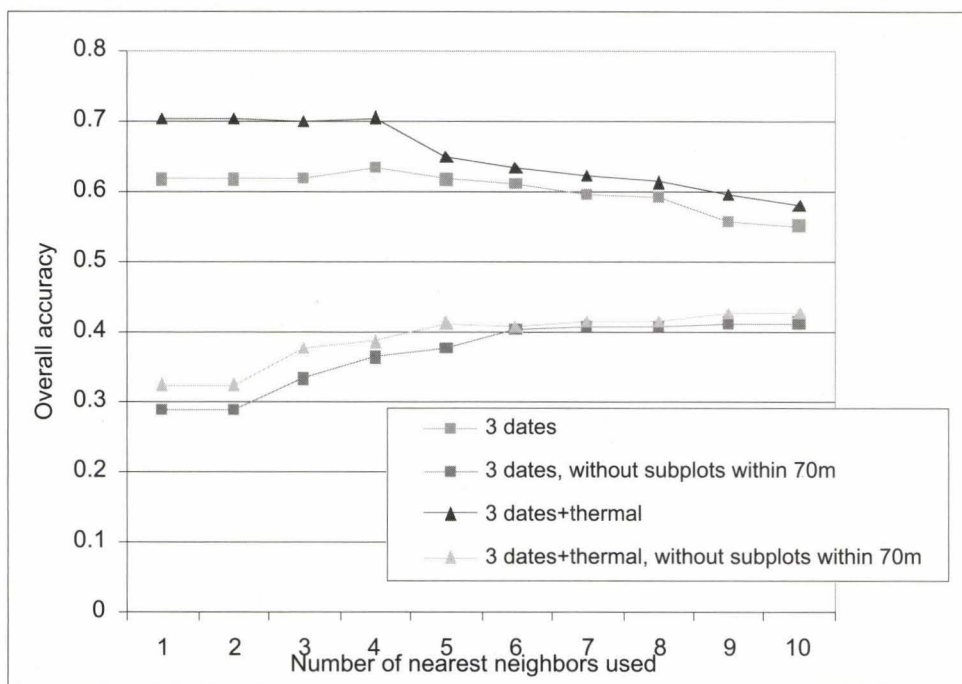


Figure 6.—Accuracy of cover type classification with and without thermal bands, 717 subplots.

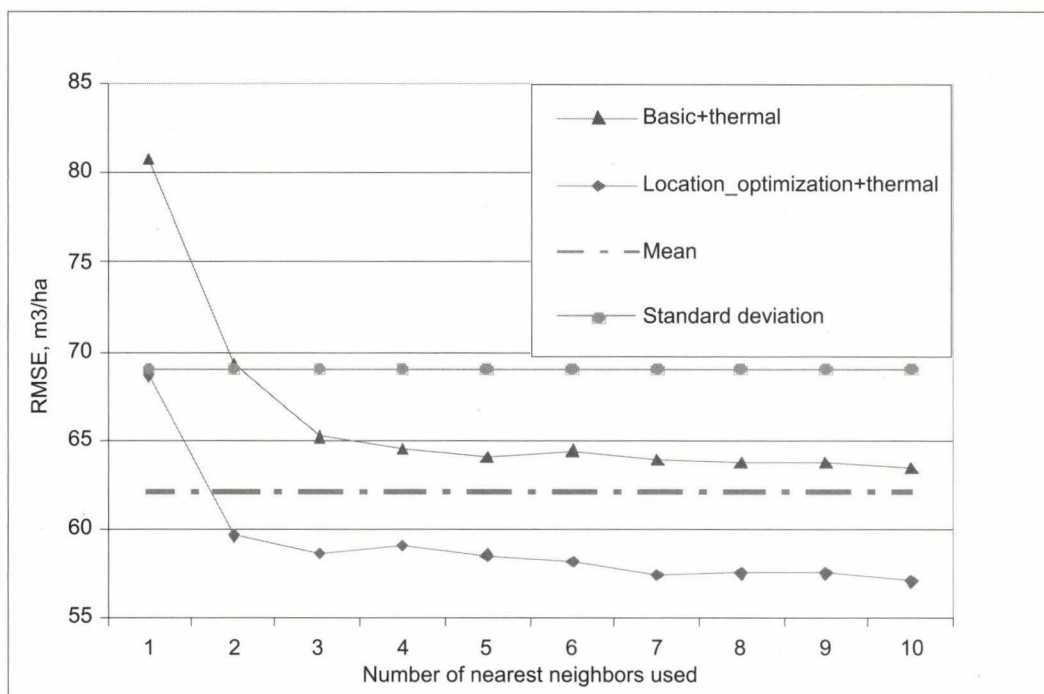


Figure 7.—Effect of plot location optimization on volume estimation RMSEs, 717 subplots.

small. Figure 7 describes the effect of plot location optimization on volume estimation RMSE. Note that plot location optimization was always superior to no optimization.

k-NN and Segmentation Approaches

Using segmentation with the k-NN method has not received much attention in research. In theory there are two ways to use segmentation with k-NN. First, one could conduct a k-NN assignment of field plot data and then segment the results and label the resulting polygons by average or modal k-NN values. This could be an effective way to produce preliminary stand delineations and cover type maps. Alternatively, one could segment the image and then conduct a modified k-NN estimation on a polygon or other basis to assign field plot data.

In our studies, two different segmentation algorithms that have been successfully used in Scandinavian forests (Haapanen and Pekkarinen 2000, Hagner 1990) have been implemented (in software) and are undergoing testing:

- (1) T-ratio method by Hagner (1990)
- (2) Narendra and Goldberg method (1980)

These two algorithms can also be used one after another to improve results: the segmentation can be run with Narendra and Goldberg's method and then fine tuned with the T-ratio method. Our studies have just started and there are few results to present at this point, except that realistic appearing stand- level segmentation now seems feasible for section, township, and perhaps larger areas with Landsat TM level resolution.

NEXT STEPS

Plans for the near future include extending k-NN methods to incorporate a second year of FIA data, which will allow a larger sample size on both a plot and subplot basis. This addition will facilitate determination of the best approaches (plot or subplot basis) to improve confusion matrices and to investigate segmentation approaches in conjunction with k-NN methods. Additionally, we plan to examine these methods for possible use in improving existing FIA design/ estimation and potential design improvements.

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ALLOMETRIC SCALING THEORY APPLIED TO FIA BIOMASS ESTIMATION

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ABSTRACT.—Tree biomass estimates in the Forest Inventory and Analysis (FIA) database are derived from numerous methodologies whose abundance and complexity raise questions about consistent results throughout the U.S. A new model based on allometric scaling theory (“WBE”) offers simplified methodology and a theoretically sound basis for improving the reliability and usefulness of biomass estimation for all tree species. Although a complete test of the WBE theory is beyond the scope of this paper, implications of the theory are explored from results of another study consistent with WBE theory. Two interesting results were found: (1) a simplified approach using 10 generalized equations is within 10 to 40 percent of FIA county-scale biomass estimates, and (2) of the two methods, FIA’s methodology appears more inconsistent from State to State.

The largest application of current biomass methodology in the U.S. is found in the Forest Inventory and Analysis (FIA) database. FIA biomass estimates are calculated either from conversion functions of merchantable volume to total tree biomass or from species-specific biomass equations. Because so many different equations and techniques are used, there is concern about equation bias confounding FIA biomass results. For example, Hansen (this volume, table 5) compared 67 tree species common to four eastern FIA regions and found that biomass estimates differed by an average of 25 to 30 percent among regions for trees of the same size and species. The test did not include a control for “known” biomass, but methodology differences among FIA regions seem a likely explanation for the observed differences among equations for the same species.

Improving FIA biomass estimates by constructing new equations would be a huge and costly undertaking because there is no theory to guide the process other than statistically subsampling for new biomass data, which would need to represent all tree species in all locations throughout the entire U.S. However, allometric scaling theory offers a possible area of research to simplify the process.

Allometric scaling is an old idea in biology—linking an organism’s size to its energy balances and structural dimensions (Niklas 1994, Peters 1983, Schmidt-Nielsen 1984)—that is being revisited with new theoretical explanation (Enquist and Niklas 2001; Enquist and others 1998, 1999, 2000; West and others 1997, 1999a, 1999b). The logarithmic model currently used for many tree biomass and volume equations (Schumacher and Hall 1933, Whittaker and Woodell 1968) is related to allometric scaling theory. However, the widespread use of the logarithmic model is generally based on empirical evidence resulting from the fitting of regression data rather than on any firm theoretical basis. The objective of this paper is to explore devising new biomass estimators through greater use of the allometric scaling theory.

First, tree biomass estimation is discussed based on recent work (Jenkins and others 2003), in which we surveyed the literature of all published biomass equations for U.S. tree species and summarized results into 10 equations based on diameter at breast height (d.b.h.). The synthesis into so few equations is consistent with allometric scaling theory or what we call the “WBE allometric-scaling model,” where WBE stands for the developers—West, Brown, and Enquist. Next, to hypothesize about the usefulness of the WBE model for FIA biomass estimation, the 10 equations were compared to FIA biomass in the Eastern U.S. (Hansen and others 1992). Because neither the 10 equations nor the FIA biomass estimates offer a satisfying measure for “true” biomass, the paper concludes with a fuller discussion of the WBE model that might be tested for improved biomass estimators.

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BIOMASS EQUATIONS

The literature contains more than 2,300 biomass equations for various wood, bark, foliage, branch, and root components for more than 100 species. However, use of these equations for consistent forest biomass estimation for all species is messy because there are many gaps among species, tree sizes, and geographic areas not covered by the equations. Furthermore, developers of these equations often caution against extrapolation beyond their study area.

As an interim solution to this problem, Jenkins and others (2003) synthesized all the published equations in a modified meta-analysis to develop new equations that could be used for similar species groups covering all U.S. species. The idea was to “average” the variation among existing equations as a way to extend the data pool for filling all the gaps. From our database of component equations, we were able to compile 315 species-specific equations to estimate total aboveground biomass from d.b.h. only, which eliminated all equations requiring more variables than d.b.h. From the species-specific equations, we generated what we called “pseudodata” within the d.b.h. ranges of the original data (fig. 1). Published equations were most numerous for hardwood and conifer species up to 70 cm d.b.h. Large-tree equations up to 150 cm d.b.h. were available only for western conifer species.

The pseudodata were used to construct 10 new total biomass equations as a summary of the literature. The 10 equations—fit to a simple log model form—included 5 equations for conifer species, 4 for hardwoods, and 1 for a woodland group including both conifer and hardwood dryland forest species (table 1). The objective of the meta-analysis was to develop an easy-to-use set of biomass equations for using FIA data to measure the amount of carbon sequestered in U.S. forests. Because the equations predicted total biomass only, we also developed generalized hardwood and conifer ratio equations to partition estimates into foliage, bark, stem wood, and coarse root components (see Jenkins and others 2003, for details).

A secondary observation from this work was a surprising similarity of pseudodata among species. Graphs of combined pseudodata showed much overlap for many species from diverse geographic areas. For example, loblolly, pinyon, and lodgepole pine species—which grow in warm/humid Southeast, hot/arid Southwest, and cool/montane northern Rocky Mountains, respectively—overlapped each other and all other pine species (fig. 2). This seems a remarkable coincidence, suggesting some underlying explanation such as the WBE model.

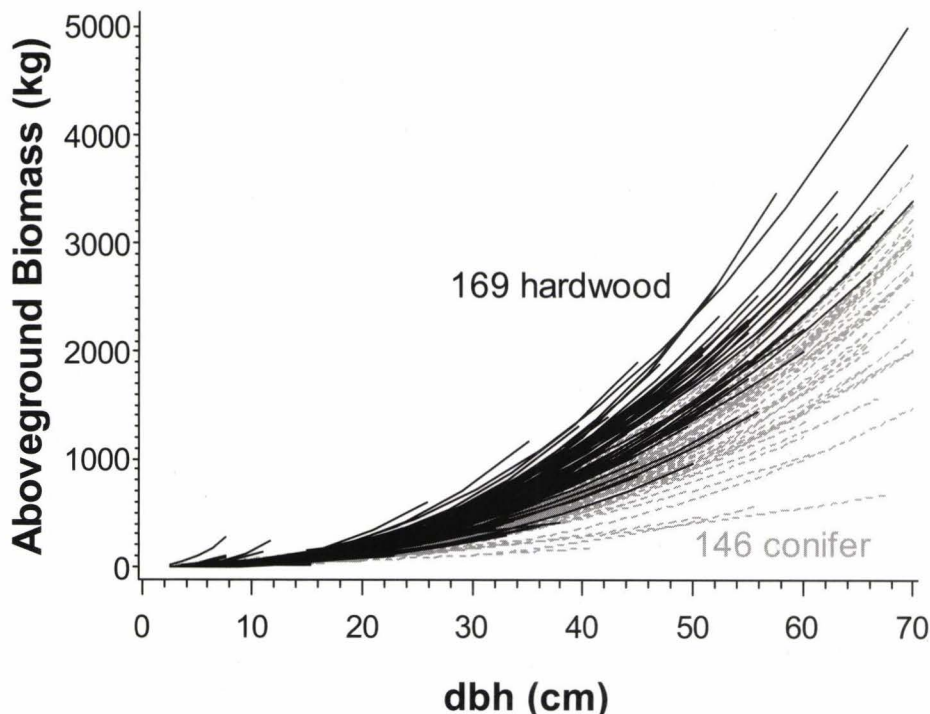


Figure 1.—Pseudodata were generated within d.b.h. ranges of the original data from 315 species-specific equations for hardwoods and conifers throughout the U.S.

Table 1. —Parameters and equations¹ for estimating total aboveground biomass for all hardwood and conifer species in the U.S. (from Jenkins and others 2003)

Species group ²		Parameters		Data points ³	Max ⁴ d.b.h. cm	RMSE ⁵ - - - log units - - -	R ²
		β_0	β_1				
Hardwood	Aspen/alder/cottonwood/willow	-2.2094	2.3867	230	70	0.507441	0.953
	Soft maple/birch	-1.9123	2.3651	316	66	0.491685	0.958
	Mixed hardwood	-2.4800	2.4835	289	56	0.360458	0.980
	Hard maple/oak/hickory/beech	-2.0127	2.4342	485	73	0.236483	0.988
Softwood	Cedar/larch	-2.0336	2.2592	196	250	0.294574	0.981
	Douglas-fir	-2.2304	2.4435	165	210	0.218712	0.992
	True fir/hemlock	-2.5384	2.4814	395	230	0.182329	0.992
	Pine	-2.5356	2.4349	331	180	0.253781	0.987
	Spruce	-2.0773	2.3323	212	250	0.250424	0.988
Woodland ⁶	Juniper/oak/mesquite	-0.7152	1.7029	61	78	0.384331	0.938

¹ Biomass equation:

$$bm = \text{Exp}(\beta_0 + \beta_1 \ln d.b.h.)$$

where

- bm = total aboveground biomass (kg) for trees 2.5-cm d.b.h. and larger
 $d.b.h.$ = diameter at breast height (cm)
 Exp = exponential function
 $\ln$ = natural log base "e" (2.718282)

² See Jenkins and others (2003) for definition of species groups and a suggested match to the FIA species list.

³ Number of data points generated from published equations (generally at 5-cm d.b.h. intervals) for parameter estimation.

⁴ Maximum d.b.h. of trees measured in published equations.

⁵ Root mean squared error or estimate of the standard deviation of the regression error term in natural log units.

⁶ Woodland group includes both hardwood and softwood species from dryland forests.

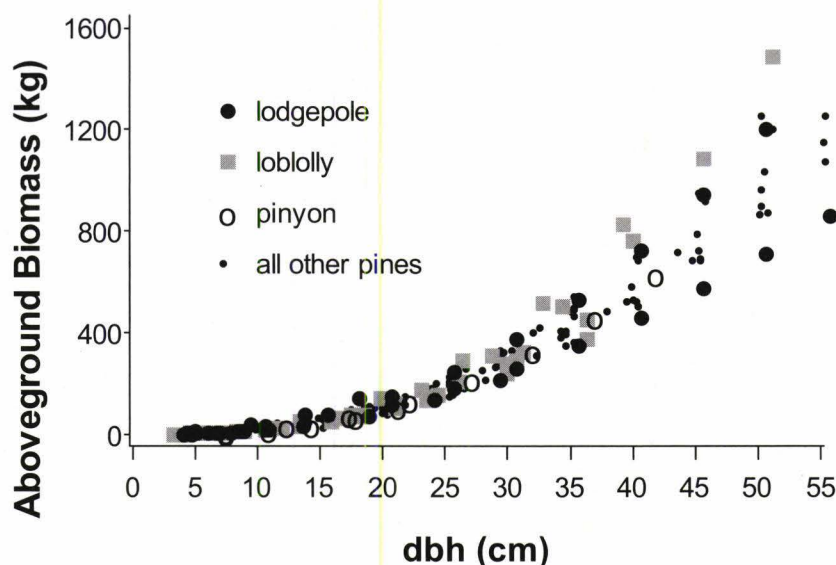


Figure 2.—There is little pattern within pseudodata generated from published biomass equations for several diverse pine species throughout the U.S. Loblolly grows in warm/humid Southeast, pinyon in hot/arid Southwest, and lodgepole in cool/montane northern Rocky Mountains.

FIA BIOMASS COMPARISON

The new 10 equations (hereafter called Jenkins estimates or Jenkins equations) were compared to the biomass estimators in the FIA database. Differences of up to 40 percent or more were revealed between FIA estimates and the new equations for a county-scale compilation (fig. 3). In each case, tree-level data were compiled for each county by the two methods; comparison was made by subtracting FIA biomass from the Jenkins estimate, then dividing by Jenkins and multiplying by 100 to express as a percentage. Except for Georgia, the FIA estimates for most of the Southern States were within 10 percent of the Jenkins estimates, but the differences between the two methods increased to 40 percent or more when moving north and west.

Since the Jenkins equations are constant for all States, abrupt changes at State boundaries (such as for Georgia, New York, and Indiana) cause special concern because they create the impression that FIA methods change abruptly at State or FIA unit boundaries. A more speckled map showing county-to-county variation within States, depending on species composition, would have been expected if the FIA equations had simply been more precise. It is difficult to say which equations are better, but the FIA estimates do seem to include some State-to-State variation due to methodology, whereas the Jenkins equations are at least consistent in methodology throughout.

Although the comparison lacks a control for "true" biomass, it does show that: (1) there is inconsistency in FIA biomass estimates, and (2) the Jenkins equations seem close enough to the FIA biomass estimates to warrant further study of simplified methods. Furthermore, a "repair task" to fix inconsistencies in the FIA database or construct new species-specific equations to fill gaps seems daunting with the current empirical framework that allows different equation parameters for every possible species and site difference. Perhaps it is time to seek a general theoretical framework to make the task more manageable. Allometric scaling theory might help in this regard.

ALLOMETRIC SCALING THEORY

Whether used with plants or animals, the WBE model applies to naturally occurring networks that carry sustaining fluids in organisms, in which each small part of the network is a self-similar replicate of the whole (fig. 4). Two key tenets

of the theory are (1) individual cells are of similar size in all organisms, and (2) no matter what the size of the organism, the ends of the fractal network are the same size. Tree leaves are an example of the second tenet; leaves are at the end of the fractal branching network in trees, and leaves for a given species are roughly the same size no matter the tree age. The WBE model offers many proportionalities relating components of structure and function, and it is these proportionalities that appeal to applied modelers.

The WBE framework describes biomass with the following equation:

$$B_{TA} = C(p \text{ d.b.h.}^{8/3}) \quad (1)$$

where

B_{TA} = total aboveground dry weight biomass

C = proportionality constant

p = specific gravity of aboveground material

$8/3$ = scaling exponent, derived from earlier studies
where d.b.h. scales as volume to the $3/8$ power
(Enquist and others 1998)

d.b.h. = stem diameter at breast height.

The WBE framework is not too unlike what is normally used for biomass estimation, except for two key differences: (1) the exponent on d.b.h. is fixed to $8/3$, and (2) specific gravity is included in the model. By specific gravity we mean total tree specific gravity (an average of wood, bark, branches, and leaves), which is not often measured. Generally in an allometric equation, both the proportionality constant (C) and the scaling ($8/3$) exponent would be estimated from accurately measured biomass data. In this case, we need only estimate C and use an appropriate specific gravity.

Applying the WBE biomass framework (equation 1) to the Jenkins equations (table 1) does make the WBE model seem plausible. In 9 of the 10 equations, the scaling parameter estimated from pseudodata is remarkably close to the theoretical $8/3$ or 2.67. However, all of the scaling exponents are lower than the theoretical 2.67, which warrants further testing before drawing conclusions. A more formal test, involving confidence intervals around the scaling exponents to test for inclusion of 2.67, does not seem useful because of the complexity of the modified meta-data analysis used to estimate the coefficients. The pseudodata have their own biases and other problems that limit usefulness for an objective test. Instead, a test of the WBE model with carefully measured tree biomass and specific gravity data seems more worthwhile.

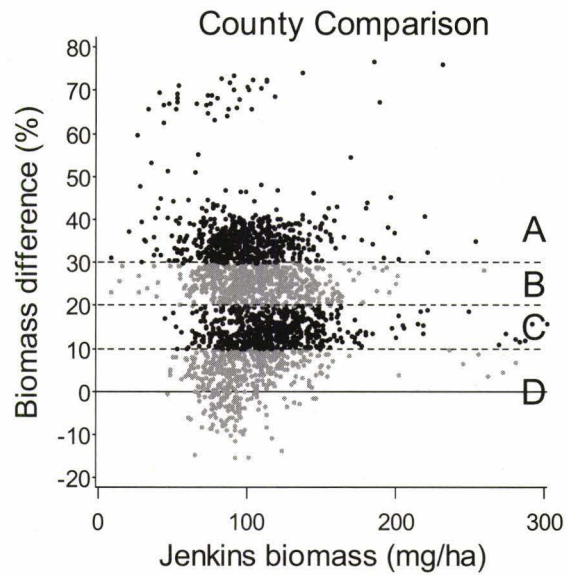
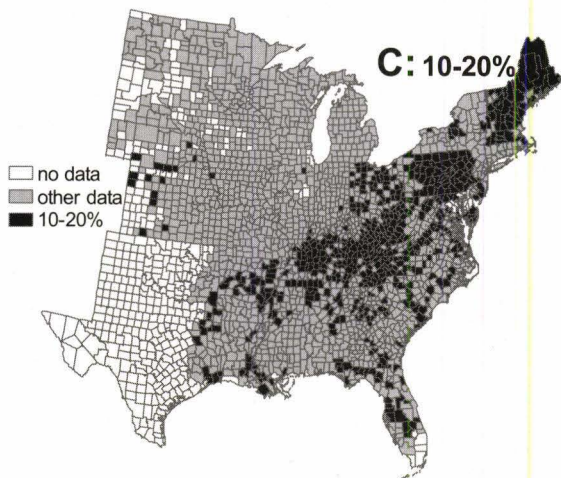
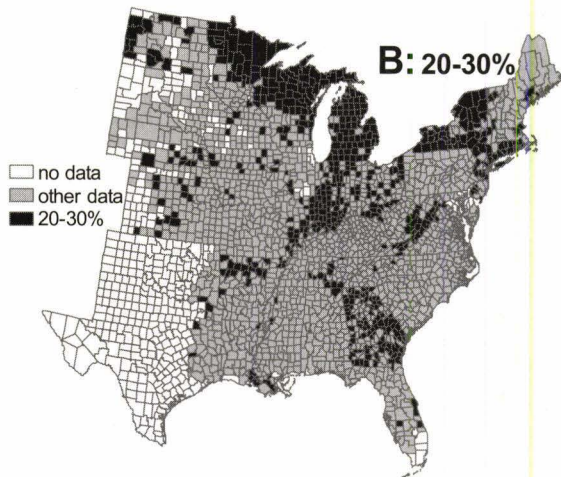
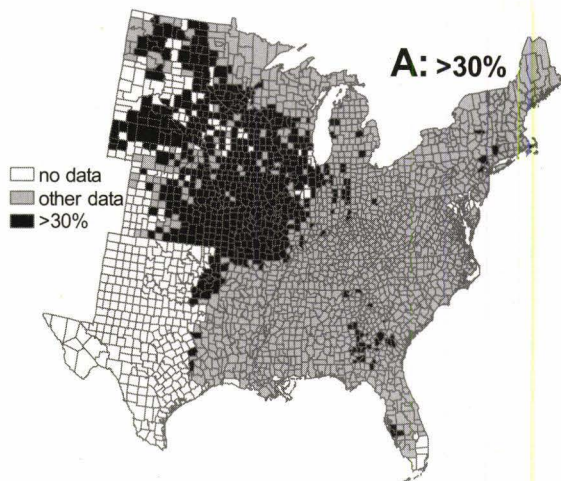
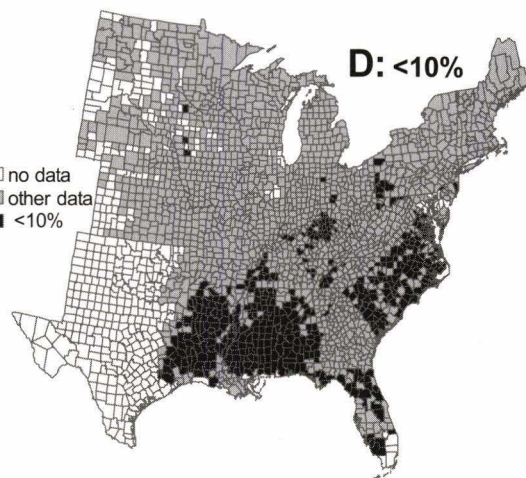
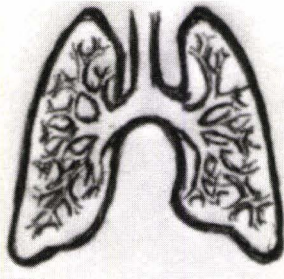


Figure 3.—County-level comparison between Jenkins and FIA volume equations (applied to same tree-level data) reveals differences in methodology that range from <10 to 80 percent depending on geographical area. The largest differences (A) are found in the Midwest, and the smallest differences (D) appear in the Southeast. Because the Jenkins equations are constant for every State, the difference pattern suggests that FIA volume methodology varies greatly from State to State. Comparison was made by subtracting FIA from Jenkins, then dividing by Jenkins and multiplying by 100 to express as a percentage.

*-37% for Cherokee County, Iowa, omitted from graph





Lung circulatory system is a self-similar fractal.



Likewise, tree branching follows a similar pattern.

Figure 4.—*The scientists who developed the scaling theory took clues from naturally occurring networks that carry sustaining fluids in both plants and animals. Each small part of the network is a self-similar replicate of the whole.*

CONCLUSION

Although thousands of equations have been published for components of tree biomass, consistent application for all species across the U.S. is difficult because most equations were developed from small local populations. However, the FIA database pieces together existing biomass methodology for nationwide estimates. The FIA approach offers a “bottom up” strategy in which each FIA unit uses the best equations or methodology for a particular State or region. Jenkins and others (in press) offer an alternative by first summarizing existing literature into 10 equations in a consistent fashion for hardwood and conifer species groups. This is a “top down” strategy, which averages equation differences within species and across similar species, and which groups species broadly enough to logically cover gaps. Comparison of the two strategies showed the most similarity in the Southern States but differences up to 40 percent or more elsewhere.

Although neither the FIA database nor the Jenkins equations offer a satisfying “true” biomass estimator, the Jenkins equations seem close enough to the FIA estimates to warrant

further study of a simplified method. Furthermore, the Jenkins equations are consistent with the notion of a generalized WBE allometric scaling model. Allometric scaling theory offers the WBE model for improved biomass estimation. Although similar to previous logarithmic models, the WBE model has one less parameter to estimate and includes a total tree specific gravity variable, which is an appealing concept for grouping large numbers of species into similar specific gravity classes.

Needed to test the WBE model is a designed experiment of field data strategically sampled at a few sites throughout the U.S. For example, biomass data might be collected with either destructive or non-destructive sampling methods (such as discussed in Gregoire and others 1995) from about 10 species of several sizes each, spanning specific gravity ranges from 0.3 to 0.8 for at least four sites in the Southeastern, Northeastern, Southwestern, and Northwestern U.S. The replications of tree size and site conditions would provide a total sample of about 120 trees. Each tree would also require subsampling for specific gravity throughout its wood, bark, branches, and foliage. If successful, results would provide biologically consistent methodology for all species, and specific gravity parameters would be used to group species.

The WBE model also offers linkage to volume estimation. Tree boles (trunks) have been characterized in geometric terms as stacked frustums of neiloids, paraboloids, and cones since the middle of the 19th century (Grey 1943). A vascular pipe model of a tree (Shinozaki and others 1964) is consistent with the middle and upper geometric models (the paraboloid and the cone) and is consistent with the WBE model of biomass. The WBE model thus should be consistent with a stem taper model. Therefore, it might be possible to develop the mathematical details of a connection between the WBE model and stem taper, and then fit the resultant joint model to data. Estimates of bole volume could then be obtained from the integral of the taper model, a standard mensurational procedure. Promising results in this endeavor may result in a major research thrust to fit the joint models regionwide or nationwide.

Lastly, if the WBE model could successfully separate bole from total biomass, there seems further opportunity for separating biomass components. Even if rough ratios for bark, branch, and foliage components are used, the WBE model would offer vast improvement over what is currently available because the largest biomass component—the bole—would be estimated quite precisely, which would limit errors to bark, branches, and foliage.

The WBE model might vastly improve the reliability, consistency, and usefulness of biomass and perhaps volume estimation across the Nation. The FIA database and all users of biomass data would benefit greatly.

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A COMPARISON OF SEVERAL TECHNIQUES FOR IMPUTING TREE LEVEL DATA

David Gartner and Greg Reams ¹

ABSTRACT.—As Forest Inventory and Analysis (FIA) changes from periodic surveys to the multipanel annual survey, new analytical methods become available. The current official statistic is the moving average. One alternative is an updated moving average. Several methods of updating plot per acre volume have been discussed previously. However, these methods may not be appropriate for updating more detailed data such as diameter distribution and species composition tables. Several methods for updating these more detailed data will be compared. Methods to be compared include imputing whole tree lists from donor plots and imputing all the individual trees for each plot. The data from the last periodic survey of Georgia and Georgia's first panel will be used to compare the different imputation methods.

Forest Inventory and Analysis units (FIA) of the USDA Forest Service have been conducting surveys of commercial forest land in the continental United States since the 1930s. Traditionally, FIA surveys have been conducted on a State-level survey cycle of from 6 to 15 years with a mode of about 10 years in the South. The 10-year cycle was considered timely enough prior to the tightening of the supply and demand relationship for wood fiber in the South (Reams and others 1999).

With the growing demand for wood products from the South, the need for more current inventory information has become apparent. This need is evidenced by the Agricultural Research, Extension, and Education Reform Act (PL 105-185) (The Farm Bill) of 1998, which congressionally mandates FIA to implement an annual inventory system nationwide.

Southern FIA is changing from single panel (periodic) whole State surveys to an interpenetrating five-panel annual survey (Reams and Van Deusen 1999). Panel denotes a sample in which the same plots are measured on two or more occasions. For those familiar with the longstanding 10-year

periodic FIA survey, the interpenetrating annual panel design is analogous to taking the large periodic survey and dividing it into five repeated smaller samples (Reams and Van Deusen 1999). The chief advantage of the annually repeated survey over the traditional periodic design is that the separate annual samples provide information about variations that occur between the periods. This results in the ability to estimate annual and secular trends.

The official FIA estimate will be a moving average using the annual survey data (Reams and others 1999). Equation 1 is the formula for the moving average, where τ is the value for the different panels.

$$\sum_{i=1}^5 \frac{\tau_{T-i}}{w_i} \quad (1)$$

However, some users of the annual survey data have suggested they would like to use data values that can be considered either made current or updated in some fashion via a statistical modeling approach. These approaches would project the oldest data forward in time by replacing the missing future panels with estimates based on data from existing panels, e.g., an updated moving average. Equation 2 is the formula for the updated moving average.

$$\sum_{i=1}^3 \frac{\tau_{T-i}}{w_i} + \sum_{i=4}^5 \frac{\hat{\tau}_{T-i+5}}{w_i} \quad (2)$$

Operational implementation of this updated moving average would not occur before year 8. Changes from panel 1 to panel 6, from panel 2 to panel 7, and from panel 3 to panel 8

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can be used to predict the changes from panel 4 to panel 9 and from panel 5 to panel 10. Figure 1 shows what data would be used, with the dotted line under the label “Updated Moving Average” representing data to be predicted.

This replacement of missing data with modeled data is referred to as imputation in the statistical literature (Rubin 1987). After data values for old or unmeasured plots have been imputed, it would be tempting to analyze a simulated-complete data set as if it were a complete data set. However, this approach would tend to understate the true variance in the estimates (Little and Smith 1987, Van Deusen 1997).

Several methods of updating plot per acre volume have been discussed (Gartner and Reams 2000). However, these methods would become very cumbersome to use for tables with many entries, such as the diameter distribution by species composition tables. Methods that impute tree-level values will be needed to create these tables.

METHODS

Data

The data used for this study are from the seventh Georgia statewide survey completed in 1997 and the first panel of the

new rotating panel system. The same plot locations are used in both systems, so that plots can be compared at two different times. The same fixed-radius plot designs were used in both surveys, allowing the tree lists from the two surveys to be compared.

The list of plots started with the plots occurring in both the seventh Georgia statewide survey and the first annual panel. All plots with more than one condition code were removed from the data set, as were all nonforested plots and all plots with harvesting. This left 419 plots available for this analysis.

Because we are attempting to simulate the conditions for the updated moving average, where two of the five panels are going to be projected forward in time, we removed the first panel data from 40 percent of the plots. We were then able to use the other 60 percent to impute the updates to the plots with missing data and to compare these imputations with the results from the full data set.

General Description of Multiple Imputation

The intent of imputation is to generate replacements for missing values from the same posterior distribution as the missing values. This is done in this study by either matching methods or modeling.

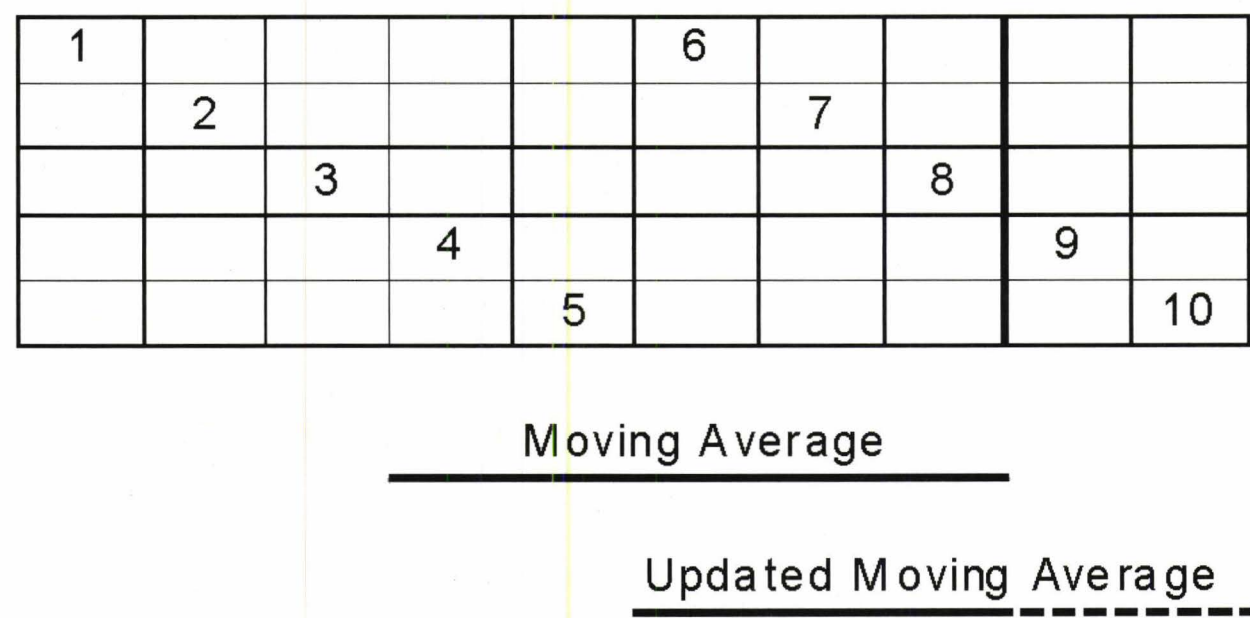


Figure 1.—Differences in the data used at year 8 for the moving average and the updated moving average.

Matching imputation methods simulate this posterior distribution by finding time 2 values in the neighborhood of the available time 1 values and randomly choosing one. This is very similar to the k-nearest neighbor approach. However, where the k-nearest neighbor uses just the mean of the neighboring values, matching imputation methods can loosely be thought of as using this mean value and adding a randomly chosen observed error component.

Figure 2 shows how matching imputation works. In the column on the left are data points containing time 2 data in

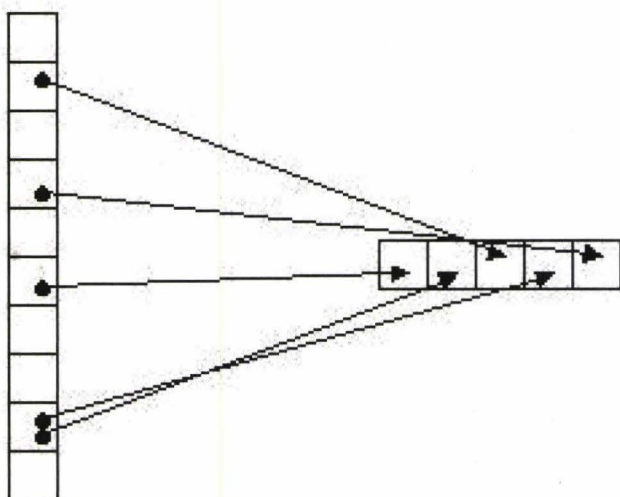


Figure 2.—How matching imputation works.

the time 1 neighborhood of the data point missing time 2 data (on right). Because we are using multiple imputation, values from the column are repeatedly drawn at random with replacement to fill in the missing data. This process is repeated for each missing data point.

Modeling imputation methods use a regression model to estimate the mean value and add an error term. However, because the regression parameters are also random variables, for the replacement values to match the posterior distributions, error terms also have to be added to the estimated parameters.

Figure 3 shows how modeling imputation works. The estimated standard deviation is the distance between the outer two lines. The estimated standard deviation does not include the variance associated with the standard error of the prediction, the distance from the center prediction line and the inner dashed lines. To incorporate this variation, most imputation programs first add random error terms to the parameters using the variance-covariance matrix, before calculating the estimated values for the missing data. Then random error terms are generated from the predicted standard error.

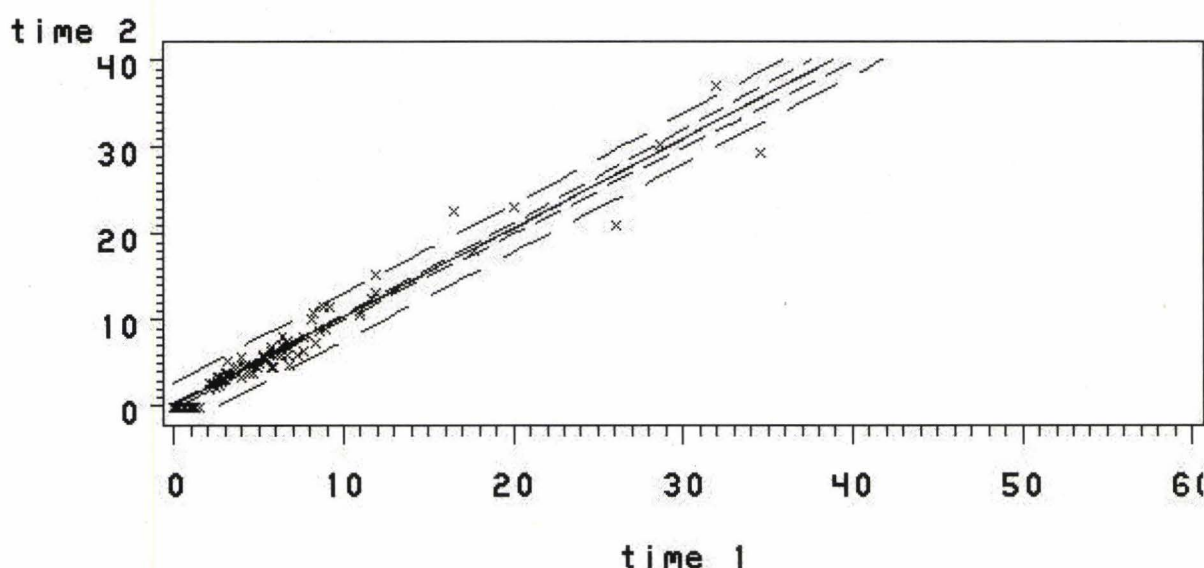


Figure 3.—Modeling imputation using linear regression, including the prediction line, and lines for the standard error of prediction and the standard deviation of the estimate.

For each run, the imputation process is repeated for all of the missing data set five times. Then the five repetitions are combined in the following manner. For each imputed data set, we calculate the statistic of interest denoted as $\hat{Q}_{*i}$. The variance of $\hat{Q}_{*i}$ is denoted as U_{*i} . The function for the estimated mean is

$$\bar{Q}_m = \sum_{i=1}^m \hat{Q}_{*i} / m \quad (3)$$

where m is the number of repetitions of the imputation process. The estimator for the variance of $\bar{Q}_m$ has two components. The first component is the average of the within-repetition variances of this mean,

$$\bar{U}_m = \sum_{i=1}^m U_{*i} / m \quad (4)$$

The second component of this variance estimator is the between-repetition variance of the $\hat{Q}_{*i}$'s,

$$B_m = \sum_{i=1}^m (\hat{Q}_{*i} - \bar{Q}_m)^2 / (m-1) \quad (5)$$

These two components are combined in the following manner:

$$T_m = \bar{U}_m + (1 + m^{-1})B_m \quad (6)$$

When standard errors are mentioned in the results for multiple imputation techniques, we use the square root of T_m . The estimated overall mean has a t distribution with mean $\bar{Q}_m$ and standard error of the square root of T_m . The degrees of freedom according to Rubin (1987) are

$$v_m = (m-1) \left[1 + \frac{\bar{U}}{(1 + m^{-1})B_m} \right]^2 \quad (7)$$

This degrees of freedom has been given a modifier for possible small sample sizes (Barnard and Rubin 1999). This modifier is

$$\hat{v}_{obs} = (1 - \gamma)v_0(v_0 + 1)/(v_0 + 3) \quad (8)$$

where $\gamma = (1 + m^{-1})B_m / T_m$ and v_0 is the degrees of freedom of the full sample if no data values were missing. The final degrees of freedom are

$$v_m^* = \left[\frac{1}{v_m} + \frac{1}{\hat{v}_{obs}} \right]^{-1} \quad (9)$$

The main advantages of multiple imputation over single imputation are that the variance caused by the process of randomly choosing donor plots is empirically estimated (equation 5) and is explicitly included in the estimate of the overall variance.

Description of Specific Imputation Techniques Used

The imputation methods used are divided into two main categories depending on the level of the variables being imputed: plot level or tree level. These two main categories are further broken down by which independent variables were used in the imputation and whether the imputation was done by matching or modeling.

Three different methods of imputing data at the plot level were used. The first method was imputing plot-level data by matching on just forest type. The second method was imputing plot-level data by grouping by forest types and matching on initial stand volumes. The third of these methods was grouping by forest type and matching by final stand volumes as predicted by SETWIGS (Bolton and Meldahl 1990). Whenever a donor plot was chosen, the donor-plot's tree list was read into the plot with missing data.

Four different methods of imputing tree-level data were used. With the tree-level imputation, three variables had to be imputed: diameter, volume, and mortality. Unfortunately, the current imputation software is not designed to impute correlated multivariate missing data. Therefore, each variable had to be imputed separately. The first method for imputing tree-level data was matching by species and on either initial diameter or volume, with final diameters and mortality being matched on initial diameter, and final volume being matched on initial volume. The second method was matching by species and on either diameter or volume like the previous method, except instead of matching on initial conditions, we matched on SETWIGS predicted values. The third method was modeling by species and on either initial diameter or initial volume. Because mortality is a discrete variable and is not very amenable to modeling by linear regression, mortality was imputed by matching on initial diameter. The final method was modeling by species on SETWIGS predictions for either diameter or volume, with mortality being imputed by matching on predicted percent mortality.

Because all of these imputation processes include randomization processes, each method was run five times and each run included five repetitions.

Tables

The different methods all generate sets of tree-level data. The performances of the different methods were compared using two of the volume tables generally provided in the State resource bulletins. Specifically, table 19 (volume by species and diameter class) and table 24 (volume by county and species type).

Comparison Statistics

The above referenced output tables 19 and 24 have several hundred entries each. Not only will each entry have its own sum, but each entry will also have a separate variance. To condense this information into something recognizable, we used the sum of the ratios of predicted mean squared error to observed variance. The formula for the sum of the ratios of mean squared error is

$$\sum_{i=1}^n \left\{ \left[\frac{(\bar{Q}_i - X_i)^2}{Var_i} \right] + \frac{T_i}{Var_i} \right\} / n \quad (10)$$

where i is the index for the table entry, $\bar{Q}$ is the average predicted sum per imputation run, X is the observed full data set sum, T_i is the variance of the imputed mean found in equation 6, and Var_i is the observed full data set variance of the sum found using the full 419 plots.

An analysis of variance was run on each of these variables, including a Tukey mean separation technique. Both tables have cells with observed values of zero. Since these cells also have variances of zero, they were deleted from the analysis. The results of the analyses of variance appear below.

RESULTS

The ANOVA showed significant differences ($p < 0.0001$) in the performance of the different methods for estimating table 19, the species by diameter class table (table 1). Imputing tree-level variables by matching on predicted values performed best. Imputing the plot-level variables also performed well. Imputing the tree-level variables by matching performed the worst.

Table 1.—Imputation results for the species by diameter class table

Model	Mean square error ratio ^a
Tree: modeling on predicted values	1.42 a
Plot: matching on initial values	2.31 ab
Plot: matching on predicted values	2.33 ab
Plot: matching by forest type	2.51 ab
Tree: modeling on initial values	2.91ab
Tree: matching on predicted values	4.36 b
Tree: matching on initial values	4.40 b

^a Treatments with the same letters are not significantly different from each other.

The ANOVA also showed significant differences ($p < 0.0001$) in the performance of the different methods for estimating table 24, the county by species group table (table 2). Imputing tree-level variables by matching on initial values performed best. Imputing tree-level variables by matching on predicted values also performed very well. Imputing the tree-level variables by matching also performed well. Imputing the plot-level variables by matching performed the worst.

The large values for the ratios for table 24 are due to occasional counties that have very similar stands in the panel data. This causes the observed variances for those counties to be very small. Therefore, any increase in variation caused by the estimation process will cause very large values to appear.

Table 2.—Imputation results for the county by species group table

Model	Mean square error ratio ^a
Tree: modeling on initial values	10.96 a
Tree: modeling on predicted values	11.17 a
Tree: matching on predicted values	12.00 a
Tree: matching on initial values	12.42 a
Plot: matching on initial values	213.66 b
Plot: matching on predicted values	224.45 b
Plot: matching by forest type	309.89 b

^a Treatments with the same letters are not significantly different from each other.

DISCUSSION

The plot-level imputation methods performed well for the species by diameter distribution table, but not for the county by species group table. The tree-level matching imputation methods did not perform as well as the other methods for the species by diameter distribution table. The tree-level modeling using the growth model projections as the independent variable performed best overall.

This study used only three-fifths of one panel of data to predict 1-year changes. The proposed implementation would use the three most recently measured panels of data to predict 5-year changes (to update the two oldest panels). The rankings of the imputation methods may not remain the same for the proposed implementation. Increasing the prediction interval from 1 year to 5 years will probably cause an increase in the variances for all of the imputation methods. However, each of the imputation methods has its own additional sources of variability that will be affected differently by changing from the scenario in this study to the proposed implementation. We suspect that the modeling methods are likely to be affected more by the change to a 5-year interval than the matching methods.

Increasing the time interval to 5 years will increase the number of plots per county. This should decrease the number of counties with very small observed variances. But it is not yet clear how much better these methods will perform for the county tables. Some caution will be needed when trying to analyze small groups of plots like counties or small ownership groups.

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VOLUME AND BIOMASS ESTIMATION IN FIA: NATIONAL CONSISTENCY VS. REGIONAL ACCURACY

Mark Hansen¹

ABSTRACT.—Volume and biomass estimates are among the most widely used data produced by the Forest Inventory and Analysis (FIA) program of the USDA Forest Service. This paper documents the various methods used by FIA in the Eastern U.S. and compares those methods for 67 species that cross regional boundaries. Four different methods currently being used by FIA to estimate the gross cubic foot volume, gross board foot volume (International 1/4-inch scale), and total gross biomass are examined. Overall, these four methods produce similar results, but large differences exist for specific species and diameters. I recommend that FIA develop a nationally consistent method for estimating volume and biomass. Users of FIA data are cautioned against making regional comparisons of volume or biomass information for small diameter trees.

Each year FIA field crews visit over ten thousand field plots and measure over one million trees on these plots. For every tree measured, estimates of volume and biomass are calculated based on these tree measurements and regional volume and biomass models. These individual tree volume and biomass estimates are used widely. They contribute to estimates of volume, biomass, growth, mortality, and removals presented in FIA reports and are accessed by many users of the FIA database (FIADB) (Miles and others 2001) via the Internet at www.ncrs.fs.fed.us/4801/fiadb/index.htm.

In recent years national consistency in methods has become a prime concern within FIA. To eliminate regional differences, FIA has adopted a national plot design that calls for taking a core set of common measurements using identical methods on all plots. One database (FIADB) was created for public access to all FIA data. This database contains tree level data including the observed tree attributes collected by the field crews such as species, diameter, height, and crown ratio and computed tree attributes such as volume and biomass.

Methods used to obtain these computed tree attributes currently vary within FIA. Each regional FIA program has its own models for producing estimates of the tree level volume

and biomass attributes in the FIADB, and in some cases these methods vary by State within a program. Because of these different methods, an identical tree measured in different locations using the same field procedures may not have the same volume or biomass estimate in the FIADB. For example, the estimated volume of a white oak that is measured to be 23.5 inches d.b.h. in southern Indiana will be different in the FIADB than an identical tree measured on the other side of the Ohio River in Kentucky. These different methods are not well documented, and regional differences are not well understood. Users of FIA volume and biomass estimates want to know how these estimates are made and if regional differences in methods affect the utility of the information.

I have limited this paper to the examination of the four different methods of gross volume and biomass estimation used by the three eastern FIA programs. Only the magnitudes of the differences between the various estimates are compared. I assume that each program selected the best available model for its region although model bias remains a major concern that I do address in this study. An estimate may be unbiased for one population (e.g., estimating total volume in a three-State area) but biased for a different area (e.g., a few counties within that three-State area). Therefore, the purpose of this paper is to simply document the different methods currently in use and to quantify differences between the methods on a set of trees that could be found in the different regions.

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FIA VOLUME AND BIOMASS ESTIMATES

FIA commonly reports seven different estimates of volume and two estimates of biomass for each tree that is sampled. These estimates are stored in the FIADB and are available via the Internet. Only three (gross cubic foot volume, gross board foot volume, and total biomass oven-dry weight) are considered here. The respective names VOLCFGRS, VOLBFGRS, and DRYBIOT are used for these estimates throughout all FIADB documentation and in this paper. These gross volume and biomass estimates form the basis for the other six estimates found in the FIADB. These other estimates are net volumes and biomass where the gross estimates are reduced for excluded portions of the tree.

The models used to compute these three attribute estimates come from various sources. They were originally obtained by fitting various nonlinear models to tree level data sets, which consisted of standard FIA tree measurements (species, diameter, height, ...) and "known" volume observations. Typically, the "known" volume observations were calculated based on detailed tree height and upper stem diameter

measurements and established regional volume tables or models. Differences exist in the model form, predictor attributes, and nonlinear regression methods used to fit the models. Each model was fit to a different data set, appropriate to the region where it is being used. In general, one model form is used for all species in a region. The model was fit for a specific species (or species group) and parameter estimates were obtained. Species were often grouped together differently in different regions. In some cases, different model forms are used for different species.

The next sections describe each of the three attributes and present the model forms and approaches to estimation used in four regions in the Eastern United States (fig. 1). The regions follow the FIA program regions (the LS and CS regions together make up the North Central FIA program region), which encompass all aspects of FIA operations including data collection, information management, and analysis and reporting of inventory results. Other details such as the fitted parameter values, methods used to fit the models, and characteristics of the data sets used in fitting are not presented here but can be found in the references given for each model.

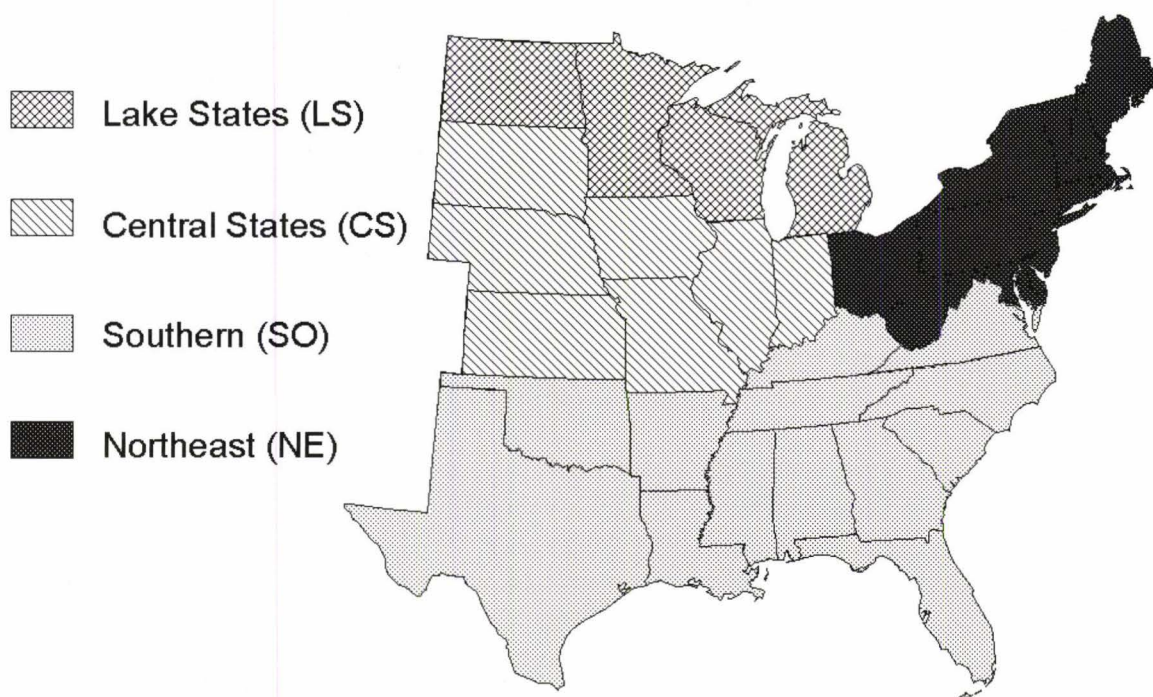


Figure 1.—Regions in the Eastern U.S. where different volume and biomass estimation methods are used.

Gross Cubic Foot Volume

Gross cubic foot volume (VOLCFGRS) is defined as the total volume inside bark of the central stem from a 1-foot stump to a minimum 4-inch top diameter-outside-bark (d.o.b.) or to where the central stem breaks into limbs all of which are less than 4.0 inches d.o.b. Although gross cubic foot volume estimates are not commonly presented in most FIA reports, this variable forms the basis for the most widely used FIA volume attribute, net cubic foot volume, reported in many core FIA tables.

In all of the models shown in this paper, the error term has been excluded for presentation purposes only. The model forms used to estimate VOLCFGRS in each of the four regions are shown in table 1. The NE and SO regions have different model forms, but both use observed diameter at breast height (d.b.h.) and bole length (BL, distance from a 1-foot stump to a 4-inch top d.o.b.) as predictor variables. In the CS region, d.b.h. and site index (SI) are used to predict VOLCFGRS. In the LS region, a combined model approach is used. First, BL is predicted based on a model that uses observed values of d.b.h., SI, and all live stand basal area (BA) as predictor variables of height to any specified d.o.b. (in this case 4 inches). A second model that uses BL (in this case predicted BL) and d.b.h. is used to make the final estimate of VOLCFGRS.

Gross Board Foot Volume

Gross board foot volume (VOLBFGRS) is defined as the total volume inside bark (International 1/4-inch rule) of the central stem of a commercial species tree of sawtimber size (9.0 inches d.b.h. minimum for softwoods, 11.0 inches d.b.h. minimum for hardwoods) from a 1-foot stump to a minimum top d.o.b. (7.0 inches for softwoods, 9.0 inches for hardwoods) or to where the central stem breaks into limbs that are all less than the minimum top d.o.b. Again, this is a gross volume with no deduction for cull and is therefore not commonly reported by FIA. VOLBFGRS forms the basis for net board foot volume, another widely used FIA attribute.

The model forms used to estimate VOLBFGRS in each of the four regions are shown in table 2. In the CS region the same model form is used for VOLCFGRS and VOLBFGRS, but of course, the parameter estimates are different. The NE region also uses the same model form for VOLCFGRS and VOLBFGRS, but in this case observed d.b.h. and saw log length (SL, distance from a 1-foot stump to a 7 (softwoods)- or 9 (hardwoods)-inch top d.o.b.) rather than observed d.b.h. and BL are the predictor variables. The approach in the LS region for VOLBFGRS is very similar to the combined model approach used to predict VOLCFGRS in that region. Initially, SL is estimated based on the same height model used in VOLCFGRS

Table 1.—Gross cubic foot volume models used by FIA

Region	Form of the model: VOLCFGRS = $f(x_1, x_2, \dots, x_n)$	Observed items: $(x_1, x_2, \dots, x_n)$	Citation
NE	$\text{VOLCFGRS} = b_1 + b_2 x_1^{b_3} + b_4 x_1^{b_5} x_2^{b_6}$	x_1 = DBH x_2 = BL	Scott 1981
SO	$\text{VOLCFGRS} = b_1 + b_2 (x_1^2 x_2)$	x_1 = DBH x_2 = BL	Royer 2001
CS	$\text{VOLCFGRS} = b_1 (x_2)^{b_2} (1 - e^{b_3 x_1^{b_4}})$	x_1 = DBH x_2 = SI	Hahn and Hansen 1991
LS	$\text{VOLCFGRS} =$ $(b_0 + b_1 x_1 + b_2 4 + b_3 x_1^2 + b_4 x_1^2 h_4 + b_5 h_4^2 + b_6 h_4^2 +$ $b_7 x_1^2 h_4^3 + b_8 x_1^2 h_4^2 4)(b_9 + b_{10} x_1)$ where h_4 = predicted BL = $4.5 + b_{11} (1 - e^{(-b_{12} x_1)})^{b_{13}} x_2^{b_{14}} \left(1.00001 - \frac{4.0}{x_1} \right)^{b_{15}} x_3^{b_{16}}$	x_1 = DBH x_2 = SI x_3 = BA	Hahn 1984

Table 2.—Gross board foot volume models used by FIA

Region	Form of the model: VOLBFGRS = $f(x_1, x_2, \dots, x_n)$	Observed items: ($x_1, x_2, \dots, x_n$)	Citation
NE	$\text{VOLBFGRS} = b_1 + b_2 x_1^{b_3} + b_4 x_1^{b_5} x_2^{b_6}$	$x_1 = \text{DBH}$ $x_2 = \text{SL}$	Scott 1979
SO	$\text{VOLBFGRS} = \text{VOLCFGRS} = \left(b_3 + b_4 \left(1 - \frac{1}{x_1} \right) \right) =$ $\left(b_1 + b_2 (x_1^2 x_2) \right) \left(b_3 + b_4 \left(1 - \frac{1}{x_1} \right) \right)$	$x_1 = \text{DBH}$ $x_2 = \text{BL}$	Royer 2001
CS	$\text{VOLBFGRS} = b_1 (x_2)^{b_2} (1 - e^{b_3 x_1^{b_4}})$	$x_1 = \text{DBH}$ $x_2 = \text{SI}$	Hahn and Hansen 1991
LS	$\text{VOLBFGRS} =$ $\left[(b_0 + b_1 x_1 + b_2 h_s + b_3 x_1^2 + b_4 x_1^2 h_s + b_5 h_s^2 + b_6 h_s x_3^2 + b_7 x_1^2 h_s^3 + b_8 x_1^2 h_s^2 x_3)(b_9 + b_{10} x_1) \right] b_{17}$ $+ b_{18} x_1 + b_{19} h_s + b_{20} x_3 + b_{21}$ where $h_s = \text{estimated SL} =$ $4.5 + b_{11} (1 - e^{(b_{12} x_1)})^{b_{13}} x_2^{b_{14}} \left(1.00001 - \frac{x_3}{x_1} \right)^{b_{15}} x_4^{b_{16}}$	$x_1 = \text{DBH}$ $x_2 = \text{SI}$ $x_3 = 7; \text{Sfwd}$ $x_3 = 9; \text{Hdwd}$ $x_4 = \text{BA}$	Hahn 1984

and observed values of d.b.h., SI, and BA. This predicted SL, together with d.b.h., is then used to predict VOLCFGRS in the final model, which is a modification of the final model for VOLCFGRS used in that region. In the SO region, a combined model approach is also used. Here, a BF/CF ratio model that uses d.b.h. as the predictor variable is multiplied by the estimated VOLCFGRS value to obtain an estimate of VOLBFGRS.

Total Biomass Oven-dry Weight

Total biomass oven-dry weight (DRYBIOT) is defined as the total oven-dry weight (pounds) of the aboveground portion of a tree 1.0 inch d.b.h. or larger, including the stump, bark, bole, top, and limbs, but excluding foliage. FIA also produces estimates of merchantable biomass, which is defined only for trees 5.0 inches d.b.h. and larger and does not include the stump, top, and limbs. In some older FIA publications, these biomass estimates were reported as green weight rather than oven-dry weight.

In all regions, model forms used for trees less than 5 inches d.b.h. differ from those used for trees 5 inches d.b.h. and larger. In the NE region, there are four different model forms, but all use d.b.h. alone to predict total biomass. One model form is used for all trees less than 5 inches d.b.h. For larger trees, one of three models is used depending on the species. For trees less than 5 inches d.b.h., the SO region has two different species dependent models that use observed d.b.h. and total length (TL, distance from a 1-foot stump to the top of the tree) to predict DRYBIOT, and for larger trees, it has two different species dependent models, but these use observed d.b.h. and BL to predict total biomass. The approach used in both the LS and CS regions is a single combined approach. In the two regions, estimates of DRYBIOT for trees 5 inches d.b.h. and larger are based on a model that uses VOLCFGRS (in this case predicted VOLCFGRS) as the predictor variable. For trees less than 5 inches d.b.h., a model based on d.b.h. is used, but it is adjusted by a factor so that at 5 inches both methods produce the same biomass. These models are all presented in table 3.

Table 3.—Total biomass oven-dry weight models used by FIA

Region	Form of the model: DRYBIOT = $f(x_1, x_2, \dots, x_n)$	Observed items: $(x_1, x_2, \dots, x_n)$	Citation
NE	For DBH ≥ 5.0 " DRYBIOT $= e^{(b_1 + b_2 \ln(x_1))} b_4$ or $= 10^{(\log_{10}(b_1) + b_2 \log_{10}(x_1))} b_4$ or $= 2.2046(b_1 + b_2 25.4x_1 + b_3 (25.4x_1)^2) b_4$ model form is species dependent b_4 is DBH class dependent For DBH < 5.0 " DRYBIOT = $e^{(.95595 + 2.42640 \ln(x_1))}$	$x_1 = \text{DBH}$	Wharton and Griffith 1998
SO	For DBH ≥ 5.0 " DRYBIOT $= b_1 + b_2 x_1^2 \left(b_3 + b_4 x_2 + \frac{b_5}{x_1^2} \right)$ or $= b_1 \left(x_1^2 \left(b_2 + b_3 x_2 + \frac{b_4}{x_1^2} \right) \right)^{b_5}$ model form is species dependent For DBH < 5.0 " DRYBIOT $= b_1 + b_2 x_1^2 x_3$ or $= b_1 (x_1^2 x_3)^{b_2}$ model form is species dependent	$x_1 = \text{DBH}$ $x_2 = \text{BL}$ $x_3 = \text{TL}$	Royer 2001
CS & LS	For DBH ≥ 5.0 " DRYBIOT $= x_2 b_4 + (b_1 + x_1 b_2) x_2 b_5 + b_3 x_1^2 b_4$ For DBH < 5.0 " DRYBIOT $= \frac{(x_3 b_4 + (b_1 + 5 b_2) x_3 b_5 + b_3 5^2 b_4)}{b_6 5^{b_7}} b_6 x_1^{b_7}$	$x_1 = \text{DBH}$ $x_2 = \text{VOLCFGRS}$ $x_3 = \text{VOLCFGRS}$ of a 5" DBH tree	Hahn 1984 and Smith 1985

METHODS AND DATA

Sixty-seven species were considered in this study. Only species common to the three regions that share a common border (CS, SO, NE) were selected. A species was included in the study only if there were at least 25 live tally trees 5.0 inches d.b.h. or larger of that species in each of the three regions in the FIADB, and only if the species occurred on at least three inventory plots in each of the three regions. The average BA and SI of FIA ground plots where the species occurred were also computed. These data are shown in table

4 along with the mean d.b.h., maximum d.b.h., and third quartile of d.b.h. for trees 5.0 inches d.b.h. and larger.

Using the mean BA and SI in table 4 and the height model portion of the LS volume model, I generated a data set consisting of 30 tree records for each species with d.b.h. values of 1 through 30 inches. These tree records consisted of simulated observations of species, d.b.h., BA, SI, BL, SL, and TL. I then applied each of the four estimation procedures for VOLCFGRS, VOLBFGRS, and DRYBIOT to this data set. The LS procedures were applied only to species found to occur (at least

Table 4.—Mean BA (square feet per acre), mean SI (feet, base age 50 years), mean DBH (in.), third quartile DBH (in.), and maximum DBH (in.) of tree species common to all three eastern regions in the FIADB

Species	Mean BA	Mean SI	Mean DBH	3 rd qu. DBH	Max DBH	Species	Mean BA	Mean SI	Mean DBH	3 rd qu. DBH	Max DBH
Eastern Redcedar	89.1	59.4	8.1	9.4	51.0	Yellow-Poplar	122.1	68.6	13.6	17.1	59.1
Shortleaf Pine	112.7	59.2	10.0	12.0	32.8	Osage-Orange	89.5	67.8	10.1	12.0	50.0
Eastern White Pine	118.0	59.7	13.9	17.9	48.1	Apple Sp.	77.3	69.6	8.1	9.0	34.7
Loblolly Pine	125.2	68.4	9.9	12.2	43.1	Water Tupelo	251.5	63.6	15.6	18.9	89.5
Virginia Pine	119.1	51.9	9.3	11.2	45.4	Blackgum	112.7	63.2	10.0	12.4	35.7
Eastern Hemlock	132.9	57.8	12.7	16.0	41.5	Ironwood	109.4	65.9	7.2	8.0	28.0
Boxelder	98.5	70.8	11.4	14.0	43.1	Sycamore	100.7	76.5	16.9	21.6	66.9
Black Maple	92.1	73.9	13.3	16.6	40.1	Balsam Poplar	96.5	62.6	10.6	12.8	47.2
Striped Maple	112.6	46.5	6.2	6.7	14.7	East.ern Cottonwood	106.9	73.5	21.2	26.9	83.9
Red Maple	117.2	62.3	10.3	12.5	59.0	Bigtooth Aspen	109.5	69.9	10.9	13.0	50.8
Silver Maple	114.9	81.4	16.3	20.4	75.0	Black Cherry	122.9	70.8	9.9	11.9	53.3
Sugar Maple	113.9	66.5	11.5	14.4	55.0	White Oak	100.4	61.3	13.3	16.5	72.0
Ohio Buckeye	97.7	76.4	9.8	11.8	26.1	Swamp White Oak	100.7	74.1	16.2	21.2	49.3
Ailanthus	103.5	56.8	8.4	9.7	21.3	Scarlet Oak	101.3	54.8	12.3	15.3	48.1
Yellow Birch	121.2	57.5	12.5	15.6	49.1	Southern Red Oak	102.1	61.0	12.0	15.0	46.5
River Birch	106.0	78.6	11.5	14.1	47.6	Cherrybark Oak	111.3	68.2	16.6	20.9	55.5
Musclewood	110.9	66.7	7.3	8.2	21.9	Shingle Oak	89.7	72.4	12.0	15.1	51.7
Bitternut Hickory	97.4	75.4	10.8	13.1	42.6	Bur Oak	94.2	58.6	13.8	17.3	63.1
Pignut Hickory	96.6	72.0	10.9	13.4	68.2	Swamp Chestnut Oak	113.1	64.3	14.9	19.0	55.8
Shagbark Hickory	94.1	70.5	11.0	13.5	50.4	Chinkapin Oak	90.3	60.6	12.5	15.4	41.0
Mockernut Hickory	94.0	71.9	10.3	12.7	37.2	Pin Oak	100.7	78.7	16.5	21.0	57.0
Hackberry	101.7	72.6	12.2	15.2	53.5	Willow Oak	113.6	64.1	14.4	18.2	52.8
Eastern Redbud	93.2	70.1	6.8	7.4	29.1	Chestnut Oak	113.9	50.1	13.0	16.2	52.7
Flowering Dogwood	114.3	67.9	6.2	6.6	49.1	Northern Red Oak	105.8	63.7	14.1	17.4	76.8
Hawthorn	95.9	80.3	6.9	7.6	21.7	Post Oak	91.0	57.5	11.0	13.5	53.4
Common Persimmon	103.9	71.0	7.8	8.9	28.1	Black Oak	94.8	63.7	13.6	16.7	84.0
American Beech	110.3	60.7	13.3	17.3	87.0	Black Locust	107.3	64.8	10.8	13.1	47.2
White Ash	105.1	73.0	11.5	14.2	56.2	Black Willow	98.6	75.6	14.1	17.3	88.9
Green Ash	100.4	68.9	11.5	14.2	52.4	Sassafras	107.8	77.5	8.4	9.8	40.0
Blue Ash	96.9	68.6	9.9	11.4	32.4	American Basswood	115.4	67.9	12.2	14.8	58.8
Honeylocust	86.7	72.0	12.8	15.9	48.6	American Elm	92.9	68.3	11.9	14.7	61.9
Butternut	91.8	70.1	12.2	15.0	31.7	Slippery Elm	96.9	74.4	11.1	13.5	55.2
Black Walnut	92.1	70.7	12.0	14.7	45.5	Rock Elm	95.6	66.4	11.2	14.3	37.3
Sweetgum	158.4	69.5	10.4	12.9	50.2						

25 trees and 3 plots) in States in that region. VOLBFGRS estimation was not done for species where the FIADB did not contain at least 25 live tally sawtimber size trees in each of the three regions. This reduced the number of species from the 67 available for the analysis of VOLCFGRS and DRYBIOT to 55 used to compare VOLBFGRS among the regions.

RESULTS AND ANALYSIS

Figures 2 and 3 show the VOLCFGRS data for black cherry and chestnut oak. For each simulated tree, the estimated volume using each of the four regional models is plotted against d.b.h. In black cherry, the differences between methods were among the largest I found, and in chestnut oak, the differences were about as small as I found. These graphs show the range of the values FIA would report for VOLCFGRS of sampled trees with identical measurements but occurring in four different States. In figure 2, at 20 inches d.b.h. the four values for black cherry range from 58.4 to 76.8 cubic feet, a range of 28 percent of the average of the four values, and in figure 3, the range for a 20-inch chestnut oak is 46.3 to 53.7 or 12.7 percent. Similar graphs were examined for all species and estimators.

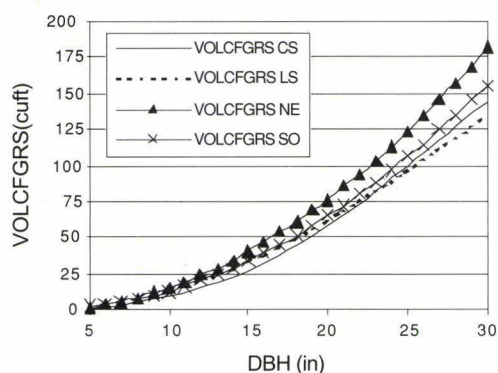


Figure 2.—Estimated gross cubic foot volume of black cherry (BA = 122.9, SI = 70.8) using the four different regional FIA approaches to volume estimation.

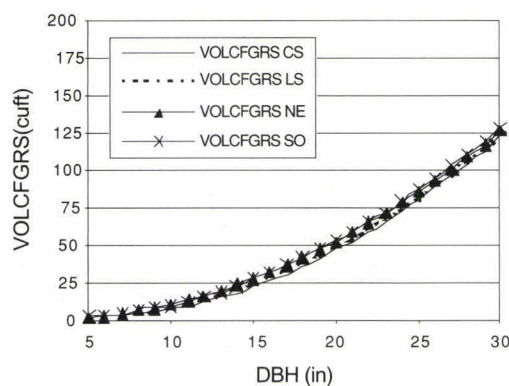


Figure 3.—Estimated gross cubic foot volume of chestnut oak (BA = 113.9, SI = 50.1) using the four different regional FIA approaches to volume estimation.

The results shown in figures 2 and 3 are typical of the ranges seen in other species and for VOLBFGRS and DRYBIOT.

Range observations, expressed as a percentage of the mean of the four estimates (or mean of the three estimates in the case of species that do not occur in the LS region) are presented in table 5 for selected diameters. Ranges of over 50 percent are not uncommon, especially for small diameter values.

Examination of graphs similar to figures 2 and 3 for all species indicated some regional trends that are also apparent in table 6. The table summarizes the number of species where each regional approach produced the maximum or minimum value for identical trees. For example, the top row of table 6 indicates that for 6-inch-d.b.h. trees, in 60 of the 67 species the SO models produced values greater than the other three regional models, and in 60 of the 67 species the CS model produced values less than the other three regional models.

For almost all species, the CS VOLCFGRS model produced the lowest value of the four methods for small diameter trees. For larger diameter trees, the LS VOLCFGRS model most frequently produced the lowest values. In very few species did either the NE or SO models produce the minimum of the four values. The SO model almost always produced the largest value for 6-inch diameter trees. Above 6 inches, the NE model most frequently produced the maximum value, but the dominance of the NE model was most pronounced in the middle diameters (9-21 inches). For very large trees, all the models except the LS model had a fair number of species where they produced the maximum value.

For VOLBFGRS, the trend is totally different. For smaller diameter sawtimber trees (12 and 15 inches d.b.h.), the LS and CS models most frequently produced the maximum values and the NE and SO most frequently produced the minimum value. In the larger diameter classes, the LS model most often produced the minimum value. The largest values were most often produced by the NE model, which seldom produced the largest value in smaller sawtimber trees.

For DRYBIOT, there is a different trend than in either VOLCFGRS or VOLBFGRS. For small diameter trees, the SO model most often produced the maximum values and the NE model most often produced the minimum values. For larger diameter trees no single model dominated either the minimum or maximum values, but the NE and SO produced most of the maximums and the LS produced most of the minimums.

Table 5.—Range of FIA volume and biomass estimates expressed as a percent of the mean among the different volume estimation methods for species common to at least three regions

Species	DRYBIOT					VOLCFGRS				VOLBFGRS		
	DBH					DBH				DBH		
	1 in.	6 in.	11 in.	16 in.	26 in.	6 in.	11 in.	16 in.	26 in.	11in.	16 in.	26 in.
Eastern Redcedar	15.1	49.3	47.5	45.6	36.3	35.4	33.6	33.8	34.3	60.2	55.0	73.3
Shortleaf Pine	26.1	35.6	71.1	82.6	87.8	22.4	18.5	19.2	25.6	22.4	35.7	51.8
Eastern White Pine	38.9	58.7	54.3	49.8	39.1	56.8	32.8	30.7	27.4	15.6	32.1	40.6
Loblolly Pine	24.9	57.2	72.1	79.5	82.6	21.4	16.1	12.2	19.2	23.8	30.6	47.9
Virginia Pine	77.6	70.2	56.7	59.2	57.5	41.4	27.4	27.5	33.4	19.9	33.0	45.5
Eastern Hemlock	54.0	44.5	49.5	47.5	32.3	32.0	22.5	12.5	8.0	21.4	8.3	15.5
Boxelder	103.3	51.1	32.2	28.6	51.5	62.7	25.7	18.2	17.7	26.1	8.6	13.0
Black Maple	53.5	41.3	46.2	47.1	44.8	33.2	22.6	16.0	13.4			
Striped Maple	85.3	46.2	39.4	43.1	45.3	56.7	23.6	20.6	24.0			
Red Maple	16.8	27.2	26.7	20.8	19.3	51.0	27.9	18.6	16.8	30.8	12.5	15.0
Silver Maple	22.0	22.3	24.0	14.7	7.4	42.9	33.6	24.5	13.1	31.0	11.9	11.7
Sugar Maple	75.3	10.7	13.0	21.2	30.5	32.7	27.5	18.4	15.7	26.0	8.5	14.3
Ohio Buckeye	98.4	31.2	31.7	24.3	26.3	46.1	25.6	17.4	15.6	21.1	4.7	13.4
Ailanthus	103.1	29.0	11.1	38.0	73.5	52.6	24.7	18.7	20.3			
Yellow Birch	19.3	19.7	34.6	34.3	30.7	48.6	34.8	26.6	27.9	23.8	8.3	17.8
River Birch	85.9	40.6	55.3	53.4	47.9	75.5	43.5	29.6	15.5	9.5	14.7	16.0
Musclewood	123.4	28.7	7.5	37.5	77.8	52.1	25.3	16.6	16.6			
Bitternut Hickory	72.4	19.5	23.3	22.5	18.4	15.7	27.5	18.7	13.5	47.3	16.0	11.2
Pignut Hickory	78.5	12.4	11.4	7.3	11.8	15.9	27.6	19.4	13.5	46.9	16.3	11.9
Shagbark Hickory	74.7	20.4	17.1	10.8	7.3	14.8	29.1	20.8	14.4	43.2	11.5	12.4
Mockernut Hickory	75.1	20.9	17.8	11.2	6.8	14.8	29.1	20.9	14.5	43.1	11.2	12.1
Hackberry	15.3	33.3	31.5	22.3	15.5	57.4	31.3	20.6	8.9	32.4	11.0	8.8
Eastern Redbud	82.0	27.7	4.3	22.9	44.2	51.9	25.3	16.1	15.8			
Flowering Dogwood	118.1	33.9	39.6	52.0	74.8	40.0	25.5	18.6	18.2			
Hawthorn	128.0	31.2	4.1	32.0	71.6	51.7	25.8	14.2	12.5			
Common												
Persimmon	107.3	43.6	37.1	50.8	73.8	35.5	26.2	18.5	17.8	29.0	20.8	23.1
American Beech	28.0	22.2	19.1	19.3	26.9	55.7	39.5	29.8	26.7	18.5	31.5	50.4
White Ash	22.8	12.9	16.8	25.9	38.9	60.9	36.8	25.3	18.8	24.2	6.6	12.4
Green Ash	22.8	25.1	30.4	25.7	36.9	61.2	36.6	25.1	18.5	24.8	6.1	11.8
Blue Ash	14.8	26.3	24.9	17.2	22.8	59.7	35.9	25.1	19.1			
Honeylocust	110.1	58.1	47.0	51.5	55.1	40.0	25.5	17.9	17.3	21.6	11.5	13.4
Butternut	34.3	35.0	38.1	32.5	57.1	58.8	30.1	17.8	15.1	44.1	16.1	14.4
Black Walnut	19.6	34.0	45.2	45.1	41.4	34.3	30.3	23.4	16.8	41.6	27.8	28.3
Sweetgum	39.9	20.1	22.9	18.0	14.9	43.5	36.2	22.7	8.6	23.1	12.8	18.9
Yellow-Poplar	39.1	30.0	32.8	25.1	22.5	34.4	27.0	19.6	24.4	34.2	13.4	17.1
Osage-Orange	123.5	28.5	7.3	37.2	77.5	52.0	25.2	16.5	16.6	23.8	8.9	12.0
Apple Sp.	80.9	26.6	16.8	36.4	62.2	51.8	25.1	16.2	16.2			
Water Tupelo	77.6	22.0	18.9	12.9	10.6	79.3	35.6	23.6	25.3	62.7	30.0	25.8
Blackgum	74.2	18.2	10.8	7.0	15.4	66.1	34.6	20.9	10.6	22.5	1.7	6.6
Ironwood	91.5	27.0	31.0	58.6	95.3	52.2	25.2	16.8	16.9	24.1	9.3	12.4
Sycamore	29.7	9.9	13.2	10.6	13.6	65.6	12.9	1.6	16.8	40.2	20.7	19.7
Balsam Poplar	53.2	11.9	22.3	23.7	49.3	43.8	34.0	28.0	25.5	33.3	9.8	31.1
Eastern												
Cottonwood	52.6	22.0	32.8	28.9	28.5	45.6	28.7	23.5	14.9	35.1	20.7	22.3
Bigtooth Aspen	92.1	18.4	27.5	27.2	45.5	46.2	35.4	28.7	25.8			
Black Cherry	49.5	40.0	27.7	12.2	18.4	58.1	48.2	36.0	27.2	36.2	19.8	29.8
White Oak	101.5	40.1	31.3	19.2	14.2	32.9	24.7	17.9	11.8	33.2	2.4	10.7
Swamp White Oak	85.0	20.9	14.5	8.2	23.5	36.7	24.9	17.5	10.0	34.2	2.8	10.4
Scarlet Oak	31.1	19.2	23.7	19.5	18.4	28.3	26.4	20.3	16.5	35.7	13.6	18.7
Southern Red Oak	32.1	21.4	11.5	22.2	35.8	27.7	27.4	19.0	13.8	35.2	13.2	15.7
Cherrybark Oak	106.0	40.9	36.7	27.4	16.5	48.6	25.9	19.8	9.3			
Shingle Oak	41.1	13.6	25.1	20.4	16.3	35.6	27.5	16.5	10.0	34.4	11.2	11.5
Bur Oak	41.4	13.5	7.8	15.4	23.4	36.9	24.3	16.8	11.7	33.4	3.6	10.4

Table 5 (continued)

Species	DRYBIOT					VOLCFGRS				VOLBFGRS		
	DBH					DBH				DBH		
	1 in.	6 in.	11 in.	16 in.	26 in.	6 in.	11 in.	16 in.	26 in.	11 in.	16 in.	26 in.
Swamp Chestnut												
Oak	58.0	20.1	24.1	20.9	12.5	50.2	25.7	18.3	10.5	32.9	3.6	15.5
Chinkapin Oak	80.7	21.1	6.6	10.2	31.4	36.5	24.1	16.6	11.5	33.9	3.9	10.0
Pin Oak	62.4	22.0	21.8	12.7	26.9	36.1	28.5	17.3	8.1	33.1	9.6	7.7
Willow Oak	78.4	38.0	33.9	19.5	22.4	46.7	27.8	17.7	11.3	33.8	11.9	16.3
Chestnut Oak	65.6	22.1	14.8	2.8	14.4	34.1	26.4	18.0	6.9	33.2	15.7	6.7
Northern Red Oak	94.7	25.9	18.1	10.7	26.5	25.1	25.8	19.6	7.6	36.3	10.0	7.2
Post Oak	45.0	17.2	17.6	14.4	10.1	41.2	28.4	21.0	11.8	29.0	6.3	12.8
Black Oak	36.7	31.7	28.4	16.8	15.5	16.8	27.5	18.7	13.4	42.5	20.9	18.9
Black Locust	136.9	49.0	48.9	51.0	60.2	35.1	26.3	20.5	24.9	28.9	39.4	51.8
Black Willow	54.4	23.1	29.3	32.1	50.0	46.9	18.5	14.8	8.4	47.1	17.2	12.6
Sassafras	66.8	24.4	17.2	22.7	34.9	55.2	26.4	17.1	15.5	26.3	4.4	10.4
American												
Basswood	26.9	25.3	37.6	34.3	55.0	41.1	36.5	25.5	19.6	28.5	10.9	18.1
American Elm	28.1	13.4	15.1	14.0	16.7	51.6	31.5	25.9	19.2	30.2	6.7	10.6
Slippery Elm	26.5	14.2	15.9	16.1	15.8	51.6	33.1	27.7	19.0	30.3	7.8	10.5
Rock Elm	25.4	17.7	27.1	36.4	62.5	51.8	31.4	25.8	19.2			

Table 6.—Number of common eastern species where each regional model produces the largest or smallest estimated volume or biomass on identical trees

MODEL	DBH	Number of species with maximum value				Number of species with minimum value			
		CS	LS	NE	SO	CS	LS	NE	SO
	<i>Inches</i>								
VOLCFGRS 67 species	6	0	1	6	60	60	7	0	0
	9	0	2	53	12	61	6	0	0
	12	0	0	58	9	61	6	0	0
	15	0	0	54	13	42	23	0	2
	18	1	0	52	14	28	34	1	4
	21	13	0	39	15	22	38	3	4
	24	18	0	33	16	18	42	3	4
	27	24	0	27	16	20	38	3	6
VOLBFGRS 55 species	12	26	26	0	3	1	0	30	24
	15	28	14	5	8	7	6	18	24
	18	20	5	12	18	12	19	7	17
	21	21	1	16	17	15	23	4	13
	24	16	1	22	16	13	27	4	11
	27	14	1	26	14	15	27	4	9
DRYBIOT 67 species	3	8	2	2	55	19	10	36	2
	6	6	15	8	38	26	3	34	4
	9	0	21	3	43	29	1	37	0
	12	3	9	10	45	13	8	38	8
	15	5	7	11	44	11	11	37	8
	18	7	4	18	38	6	19	31	11
	21	11	1	22	33	2	28	26	11
	24	8	2	26	31	4	33	19	11
	27	7	4	32	24	7	35	14	11

Figure 4 also points out these regional trends for this data set. Here I have averaged the estimates for each region across all species and plotted the regional deviation (as a percent of the average across all regions) against d.b.h. for each of the three estimates. For example, figure 4c indicates that the lines for the CS and LS models for VOLBFGRS closely follow each other and the lines for the NE and SO models follow each other. The NE and SO models are low for small diameters and high for the large diameters. All four models produce similar estimates for d.b.h. values of 15 to 20 inches, a typical diameter for a sawtimber tree.

There are definite differences in the estimates of gross volume and biomass by region for this particular set of “typical” tree measurements. Because the generated data set does not contain true values of volume and biomass, it is not possible to comment on the bias of these estimates. This brief analysis simply demonstrates that regional differences do exist and that these differences can be large.

DISCUSSION AND RECOMMENDATIONS

There are a number of possible causes of the regional trends in the volume and biomass models that have been demonstrated here. All of these models were developed independently. Typically a data set consisting of tree volume and biomass measurements along with predictor variable measurements was created. Nonlinear regression methods were used to fit estimated parameter values for the selected model form.

The data sets used to develop these models are all independent and created using different methods. Some data sets came from FIA data where additional tree height and upper stem diameter measurements were taken on standing trees. Other data sets came from felled tree data where measurements were taken on cut trees. In some cases both types of data were combined. Methods used to obtain the “known” volume and biomass values of these trees are not consistent across regions.

Differences in model form that exist between regions could account for some of these differences. The basic shapes of these models are somewhat different. The LS and CS models for both VOLCFGRS and VOLBFGRS have an inflection point whereas the SO and NE models do not. The specific nonlinear regression methods used to fit the model and weighting factors applied can have major impacts on the parameter values selected. Several of these models, such as the LS cubic foot volume models, the LS and SO board foot volume models, and

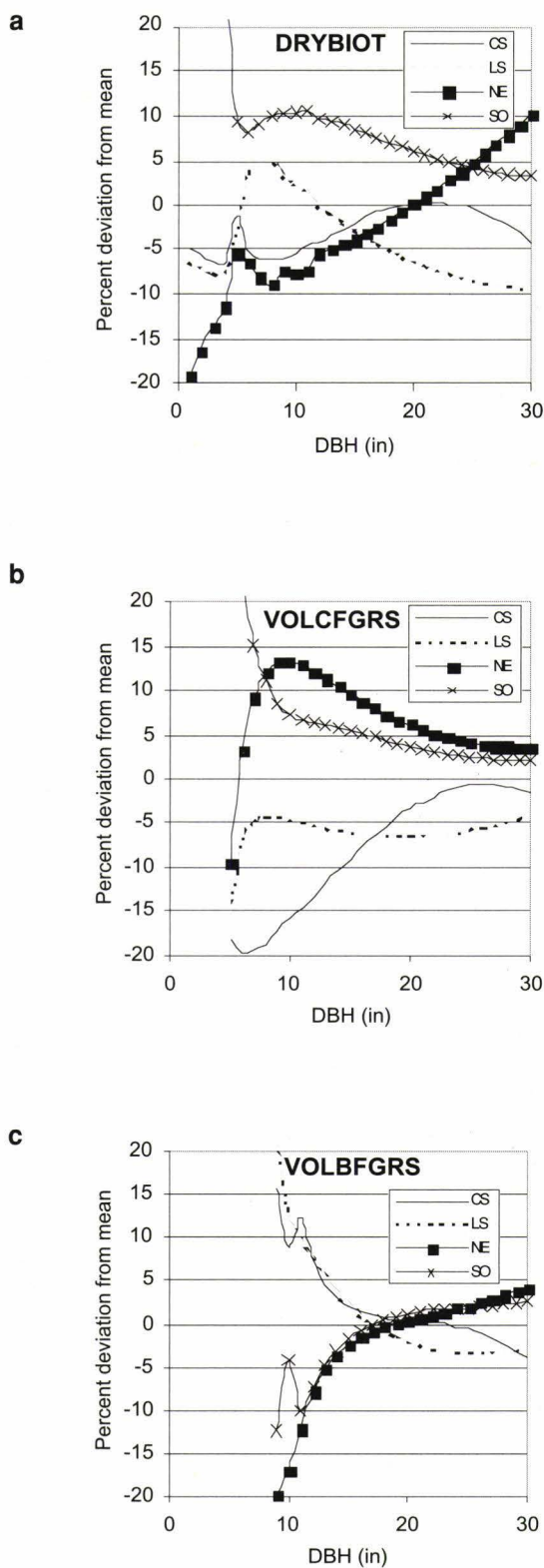


Figure 4.—Average deviation (over all common species) of the four regional estimates from the average of all four regional estimates by diameter.

the LS and CS biomass models, are combined models, where two different models are involved. The combined effect of the two models is difficult to assess.

FIA is currently making considerable efforts to move to consistency throughout all of its operations. Across the country, a common plot design is used and common plot and tree attributes are measured. These common data are available to all users. It seems reasonable to assume that when two trees measured in two different locations have identical measurements, they should have identical volume and biomass values, not values as different as 100 percent or more. FIA needs to move to a consistent method to estimate tree volume and biomass nationwide that uses common measurement data to estimate the volume and biomass of sample trees.

What would it take to develop a consistent system for volume and biomass estimation? This would be a major project for FIA. An approach that I would recommend is to base volume and biomass estimates on predicted stem profile or taper models. Such a system would predict the bole diameter at any height. This would enable the user to predict the gross volume of any specified segment of a tree. Associated cull estimates would be needed to make net volume estimates. Biomass estimates could be based on an allometric approach in which models for the various components of biomass (bole, bark, branches, stump, roots) are based on the gross volume in the bole plus other attributes. Such a system would eliminate the need for separate VOLCFGRS, VOLBFGRS, and DRYBIOT models that currently are in use. Inconsistencies between estimates currently exist because separate models are being used. For example, ratios like DRYBIOT:VOLCFGRS or VOLBFGRS:VOLCFGRS are often inconsistent.

Demand for biomass information is increasing. A stem profile based system with an allometric model for biomass components would have more biological basis than the empirical models now being used. All of the biomass models currently in use attempt to estimate various biomass components such as biomass in branches, primarily through percentage estimates from published information. These estimates are all very simplistic. None of the estimates of branch biomass used by FIA utilize any of the crown measurement data such as crown ratio or crown class that are being taken. Currently the ratio of branch biomass to bole biomass for a dominant tree with a large crown ratio is equal

to the same ratio for a suppressed tree with a small crown ratio given both trees have the same species and diameter.

The development of a consistent approach to volume and biomass estimation would require the construction of a database consisting of candidate predictor variables (core FIA attributes such as d.b.h., total height, crown ratio, crown class, and species taken to FIA standards) along with sufficient height and upper stem diameter measurements needed to adequately fit a good stem profile model. FIA has recently moved to a core set of common measurement attributes and not all of the core attributes (particularly total tree height) have been collected on most older FIA plots. Also, older FIA data were limited to trees measured on timberland. FIA has expanded its volume and biomass estimation to include all forest land and is currently investigating expanding estimation to include trees on nonforest lands such as urban areas. Existing FIA data would not be adequate for developing such a model.

Phase 3 (P3) plots are a small subset of the FIA field plots on which many additional attributes are being measured. By adding several upper stem diameter and height measurements to the suite of data currently being taken on these P3 plots, FIA could begin to construct the nationwide data set necessary to develop a comprehensive approach to volume and biomass estimates. Other candidate predictor measurements could also be added to the P3 suite of data for consideration as additional core attributes if they were shown to improve volume estimates. Much information is currently available for P3 plots. Most of these plots have already been measured at least once. It would be possible to stratify these P3 plots before measurement to determine which plots and trees would need to be measured in order to construct a data set with adequate representation across species, diameters, regions, and stand conditions. Most likely it would not be necessary to make additional measurements on every tree on all P3 plots.

A number of things must be considered in the development of a new system for volume and biomass estimation. Consistency over time is an important consideration. It would be necessary to apply the new system to old FIA data in all regions in order to recompute existing estimates using the new system for comparison purposes and for estimation of components of change such as growth, removals, and mortality. If the new system uses predictor variables not previously collected, then it would be necessary to estimate these new predictor variables on old plots where they were not measured.

Until FIA adopts a consistent method of volume and biomass estimation, I would caution users of FIA data to make detailed regional comparisons of volume and biomass, particularly for smaller diameter trees. With the increasing demands placed on our timber supply, the utilization and value of smaller diameter trees is increasing. Comparisons of the volume in small diameter trees between States where different volume models are being used should be avoided. If this type of information is necessary, I suggest that users compare FIA estimates of number of trees by diameter class estimates. These estimates are not affected by volume models and should be consistent across regional boundaries.

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THE EFFICACY OF USING INVENTORY DATA TO DEVELOP OPTIMAL DIAMETER INCREMENT MODELS

Don C. Bragg¹

ABSTRACT.—Most optimal tree diameter growth models have arisen through either the conceptualization of physiological processes or the adaptation of empirical increment models. However, surprisingly little effort has been invested in the melding of these approaches even though it is possible to develop theoretically sound, computationally efficient optimal tree growth models using inventory data. The Potential Relative Increment (PRI) methodology is a good example of a flexible potential growth modeling system developed under these auspices. I present a series of suggestions for ecological consistency, variable and parameter assumptions, statistical properties, data quality, and model flexibility that should be considered when developing optimal increment models, exemplified with white oak (*Quercus alba* L.) equations from the Midsouth region.

The increased utilization of ecological simulators has led to a proliferation of models designed to forecast tree growth. Several general types can be distinguished, ranging from empirical regression models to process-based theoretical constructs or other mathematical designs. The increment model of the Forest Vegetation Simulator (FVS) (Wykoff and others 1982) is a classic example of an empirical design:

$$\Delta D = \sqrt{dib^2 + dds} - dib \quad (1)$$

Following this formulation, periodic diameter increment (ΔD , in this case, inside bark growth over a 10-yr period) is a function of inside bark diameter at breast height (d.i.b.) and squared inside bark diameter (dds):

(2)

$$\ln(dds) = HAB + LOC + b_1 \cos(ASP)SL + b_2 \sin(ASP)SL + b_3 SL + b_4 SL^2 + b_5 EL + b_6 EL^2 + b_7 (CCF / 100) + b_8 \ln(DBH) + b_9 CR + b_{10} CR^2 + b_{11} (BAL / 100) + b_{12} DBH^2$$

where HAB is a habitat type constant, LOC is a location constant, ASP is stand aspect, SL is stand slope ratio, EL is stand elevation, CCF is a crown competition factor, CR is crown ratio, BAL is the total basal area of trees larger than the subject tree, DBH is diameter at breast height (d.b.h.), and b_1 to b_{12} are species-specific regression coefficients. Not every empirical model has this number of variables and coefficients, but all are usually designed to maximize statistical fit to inventory data (often using transformed independent variables). Process-based growth models assume a specific, meaningful, and mechanistic relationship between increment and the independent variable(s). This approach is increasingly popular in ecological models (e.g., Botkin and others 1972, Chertov 1990, Pacala and others 1993) because they attempt to emphasize biological

processes rather than just enumerating tree growth.

For example, some approximate photosynthesis, like Pacala and others (1993):

$$\Delta D = \frac{g_1 GLI}{g_1 / g_2 + GLI} (DBH / 2) \quad (3)$$

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where g_1 is the asymptotic growth rate of the species under high light conditions, g_2 is the slope at zero light, and GLI is the global light index (a proxy for photosynthetic potential). Most mathematical growth models (e.g., Chapman-Richards, Bertalanffy, Gompertz) associate age and tree size to realized increment. Zeide (1993) decomposed these models into two general forms, the power decline (PD) and exponential decline (ED):

$$PD: \quad \Delta D = kDBH^p a^q \quad (4)$$

$$ED: \quad \Delta D = kDBH^p e^{qa} \quad (5)$$

where a is current tree age and k , p , and q are species-specific regression coefficients ($k > 0$, $p > 0$, and $q < 0$). Key features of these models involve the expansion (e.g., DBH^p) and contraction (e.g., a^q or e^{qa}) components, which permit rapid growth when the trees are small and constrain growth as trees age (Zeide 1993).

Two philosophies on growth prediction can also be identified. One concentrates on fitting a response curve through a cloud of data points and parameterizes the resulting model to be sensitive to measured variables. Predicted increment is either adjusted upwards or downwards from the fitted curve to reflect good or poor growing conditions. The second approach defines an upper increment response curve for “ideal” growing conditions and then rescales growth downward to reflect suboptimal performance. Most empirical and mathematical models (e.g., Lessard and others 2001, Wykoff and others 1982, Zeide 1993) typify the first approach, while process models are more characteristic of the second (e.g., Botkin and others 1972, Bragg 2001a, Hahn and Leary 1979). Either approach can yield realized increment, yet there are instances when potential growth is more interesting. While not specifically designed for this task, most empirical or mathematical designs have (under the correct circumstances) a set of conditions that would produce an increment prediction analogous to optimal growth. However, their adaptation for potential increment modeling is an inefficient solution to a problem better addressed through a hybridized, inventory-based system.

The Potential Relative Increment (PRI) methodology shares many of the attributes of mathematical and process-based growth models while retaining strong empirical roots (Bragg 2001a). The PRI equation can be generalized as:

$$\Delta D_{OPT} = DBH \left(b_1 DBH^{b_2} b_3^{DBH} \right) \quad (6)$$

where b_1 , b_2 , and b_3 are species-specific non-linear regression coefficients. Note that only d.b.h. is needed to predict the potential increment (ΔD_{OPT}) of the species, which differs from other strategies that embed environmental factor(s) directly in the model (e.g., Botkin and others 1972, Pacala and others 1993, Wykoff and others 1982) or assume that tree age is known (Zeide 1993). Using the PRI methodology as an example, this paper considers the efficacy of adapting large-scale inventories to create optimal increment models by providing suggestions to assist in model development and describing the challenges and potential of inventory-based approaches.

RULES OF THUMB FOR OPTIMAL INCREMENT MODELS

As with any statistical model, a number of rules of thumb should be followed to ensure theoretical robustness and statistical reliability (and, concurrently, user confidence). The order of this list is not meant to impart any ranking of importance, but rather is intended to track the logical flow of events when developing an optimal diameter increment model.

1. An optimal increment model must be consistent with ecological theory, including reasonable assumptions about the variables and parameters involved.

In general, an ecological growth model should fit basic expectations of biological behavior. For instance, an optimal growth model should predict neither infinite nor negative growth. The first optimal growth models often included compromises between computational efficiency and ecological relevance. The resulting efforts may have seemed practical at the time, but they have imposed some unfortunate requirements. As an example, the optimal increment equation of the gap models (e.g., Botkin and others 1972, Mielke and others 1978, Shugart and West 1977) distributed potential growth along a sigmoidal function:

$$\Delta D_{OPT} = \frac{G \cdot DBH \left(1 - \frac{DBH \cdot HT}{DBH_{max} \cdot HT_{max}} \right)}{274 + 3b_2 DBH - 4b_3 DBH^2} \quad (7)$$

where maximum diameter (DBH_{max} , in centimeters) and maximum height (HT_{max} , in centimeters) are estimated from the literature, and the growth parameter (G) equals:

$$G = \frac{4HT_{\max}}{AGE_{\max}} \left\{ \ln[2(2DBH_{\max} - 1)] + \frac{\alpha}{2} \ln \left[\frac{9/4 + \alpha/2}{4DBH_{\max}^2 + 2\alpha DBH_{\max} - \alpha} \right] - \frac{\alpha + \alpha^2/2}{\sqrt{\alpha^2 + 4\alpha}} \ln \left[\frac{3 + (\alpha - \sqrt{\alpha^2 + 4\alpha})(4DBH_{\max} + \alpha + \sqrt{\alpha^2 + 4\alpha})}{3 + (\alpha + \sqrt{\alpha^2 + 4\alpha})(4DBH_{\max} + \alpha - \sqrt{\alpha^2 + 4\alpha})} \right] \right\} \quad (8)$$

when $AGE_{\max}$ is an estimate of species longevity (in years) and $\alpha = 1 - 137/HT_{\max}$. Because of some inconsistencies in the calculation of equation 8, Botkin and others (1972) approximated values of G and greatly simplified the derivation of optimal increment. Equation 7 terminates (reaches zero growth and mandatory senescence) when $DBH \times HT = DBH_{\max} \times HT_{\max}$, placing considerable importance on $DBH_{\max}$ and $HT_{\max}$. Neither of these parameters is definitively known and may not be maximized under the most favorable growing conditions. As an example, it is not unusual for some species to reach their maximum age in less than ideal environments (e.g., bristlecone pine (*Pinus longaeva* D.K. Bailey) on alpine sites or northern white-cedar (*Thuja occidentalis* L.) on cliff faces (Kelly and others 1992)).

Furthermore, the sigmoid nature of equation 7 produces two-thirds of the tree's growth under optimal conditions by half of the tree's lifespan, thus noticeably underestimating tree growth potential (Bragg 2001a), especially when $AGE_{\max}$ is large. Figure 1 contrasts the diameter growth potential for white oak (*Quercus alba* L.), using the gap model FORAR (Mielke and others 1978, assuming $G = 100.7$, $AGE_{\max} = 400$ years, $DBH_{\max} = 122$ cm, and $HT_{\max} = 3,470$ cm) and the PRI coefficients from Bragg (in preparation a). FORAR appreciably underestimated potential increment, especially for small to moderate diameter trees (fig. 1). The PRI approach eliminates most of the unnecessary ecological limitations of the gap models by providing more realistic curve shapes and not enforcing a maximum tree size.

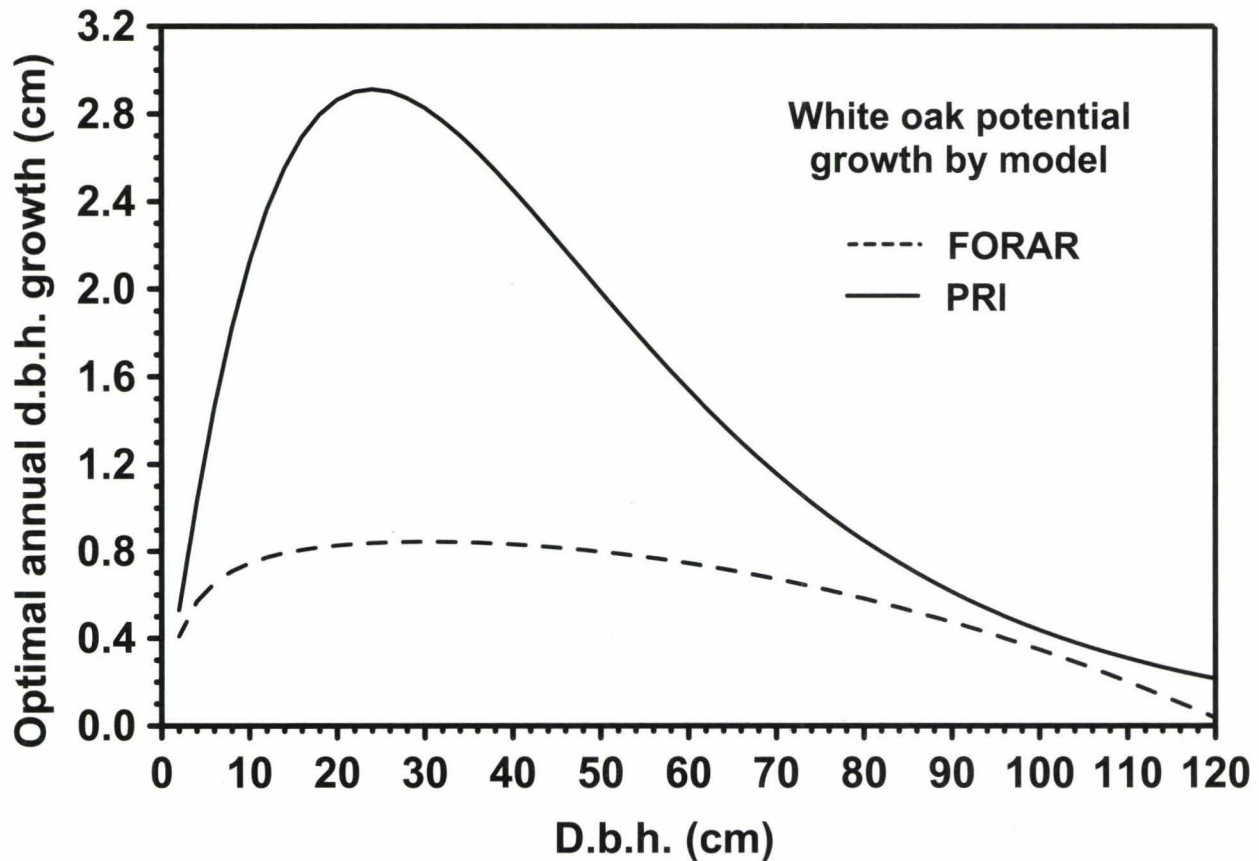


Figure 1.—Differences in white oak optimal diameter growth predicted by the PRI methodology (solid line) and the gap model equation (dashed line).

2. An optimal increment model should be statistically robust yet efficient and parsimonious.

Advances in computational ability make the development of large-scale empirical models technically possible, often giving these efforts an advantage over other designs in that hundreds or perhaps thousands of individual observations have been used to fit the equations. This large sample, collected over an extensive geographic distribution, conveys statistical power (even when many parameters are used). Inferring ecological meaning, however, from many coefficients and variables becomes challenging as more and more factors with increasingly obscure relevance are added. More parameters also do not equate to a better model design. Zeide (1991) pointed out that a high-degree polynomial with the same number of parameters as data points would provide an exact fit (fig. 2) yet would prove less biologically relevant than a simpler but noisier model (e.g., a power function) that does not attempt to explain all data variation but can be related to a known process (e.g., mitosis).

Unfortunately, many process-based optimal growth models also suffer from inadequate designs. One major problem is that their developers used very few samples of the relevant populations, thereby limiting their utility. The gap models, for example, use coefficients fit to a handful of trees (i.e., the one(s) contributing AGE_{max} , DBH_{max} , and HT_{max}), while other approaches have been developed from limited field sampling (e.g., Pacala and others 1993), thus constraining extrapolation. Other authors are quick to point out that process-based increment equations rarely (if ever) outperform empirical growth predictions (Fleming 1996, Vanclay 1994). Hence, statistical efficiency and biological relevance can sometimes fail at a critical juncture of increment model: realized performance.

The PRI methodology's compact equation form produces a parsimonious model while still considering large samples of known quality and distribution. PRI equations are directly linked to actual trees in real environments and follow reasonable rules of behavior. For example, tree diameter growth peaks at a relatively early age and then declines over

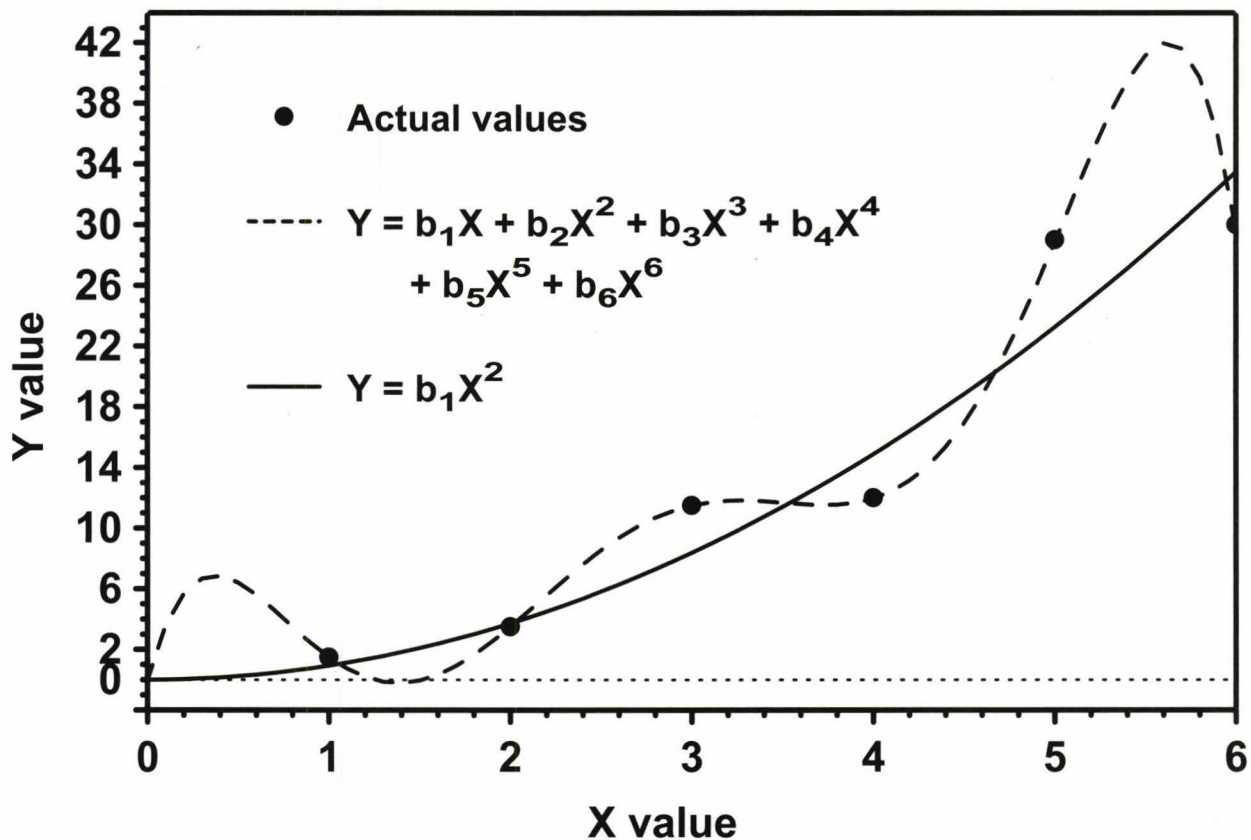


Figure 2.—Example of Zeide's (1991) assertion that simple models, while usually noisier, can be more appropriate approximations of natural systems than high-order polynomials designed to maximize fit.

time (Zeide 1993). The information used to develop PRI models, while not as formidable as in some empirical designs, is still considerable (Bragg 2001a). PRI's realized performance also does not hinge solely upon optimal increment model behavior, but rather upon the quality of the modifying functions (see next section).

3. An optimal increment model should be flexible and general in its application.

Many empirical and mathematical growth models incorporate environmental parameters directly into their equations. To illustrate this point, FVS uses up to 9 specific parameters (12 if the squared variables are included) and 12 coefficients to forecast growth. The behavior of each must be simultaneously considered to determine the appropriate combination, so interpreting parameter behavior (especially in the context of optimal growth) can be virtually impossible. As an example, beyond a small improvement in statistical fit, what is the biological significance of squared elevation or slope length? How valid is this model if the user prefers not to apply one or more of these parameters?

Even process-based designs sometimes require users to adopt assumptions they may be uncomfortable with. For instance, unless one is willing to use the global light index imbedded in the growth model of SORTIE, applying equation 3 to predict growth is not possible. Any model that explicitly includes such variable force that factor to become an integral part of the factors affecting growth performance (diameter is directly related to future increment, so it should always be included). Greater flexibility is possible in model designs that separate potential from limitations (e.g., Botkin and others 1972, Bragg 2001a, Hahn and Leary 1979). The PRI methodology considers optimal performance solely from species and current diameter, so any reasonable set of constraining functions could be used to inhibit growth.

4. The data used to develop an optimal increment model should be reliably sampled and broad in scope.

Rarely are inventories so poorly implemented that the quality of the data threatens the interpretation of the results. More likely, data limitations arise from the inadequacy of sampling conditions. Large-scale databases like the Eastwide Forest Inventory Data Base (EFIDB— Hansen and others 1992) are well suited for developing optimal increment models because of their considerable sample extent. For example, table 1 lists the 25 most abundant species in the Midsouth optimal

growth models developed by Bragg (in preparation a). The EFIDB inventory systems also have rigorous training, data quality, and accuracy standards that contribute to their reliability. While the EFIDB has supported the PRI effort to date, it is anticipated that any data set (e.g., Miles and others 2001) that includes species, original tree diameter, current tree diameter, and the remeasurement period could be similarly processed.

What makes the PRI approach unique in empirical growth modeling is that the regression coefficients are fit using a restricted subset of the increment data, rather than the entire collection. Only the trees growing the fastest within their respective diameter classes are selected for PRI analysis (fig. 3), and even these are pared down (resulting in some PRI equations being fit with 10 or fewer observations). However, depending on the species and spatial extent of the project,

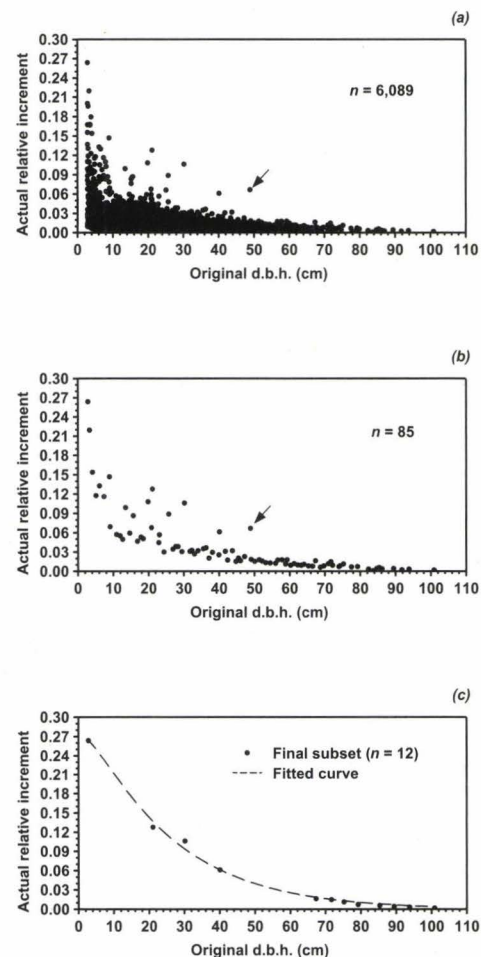


Figure 3.—PRI model derivation process for white oak in the Midsouth showing the initial data (a), a tentative selection of highest actual relative increment (b), and the final subset of points chosen to fit the equation (c). Note the outlier identified by an arrow in (a) and (b).

Table 1.—Twenty-five most abundant species used to derive Midsouth optimal diameter growth models (Bragg 2002a).

Common name	Scientific name	FIA code	n	Min. d.b.h.	Ave. d.b.h.	Max. d.b.h.	Std. dev.
Loblolly pine	<i>Pinus taeda</i> L.	131	37,672	2.8	24.8	103.4	14.42
Shortleaf pine	<i>Pinus echinata</i> Mill.	110	17,114	2.8	25.3	89.7	10.96
Post oak	<i>Quercus stellata</i> Wangenh.	835	13,308	2.8	25.2	104.4	14.02
White oak	<i>Quercus alba</i> L.	802	13,085	2.8	25.6	101.9	14.60
Sweetgum	<i>Liquidambar styraciflua</i> L.	611	12,250	2.8	24.3	111.3	14.59
Black oak	<i>Quercus velutina</i> Lam.	837	7,145	2.8	26.3	133.1	15.04
Water oak	<i>Quercus nigra</i> L.	827	5,464	2.8	34.8	140.7	20.91
Southern red oak	<i>Quercus falcata</i> Michx.	812	5,128	2.8	30.5	138.2	16.22
Blackgum	<i>Nyssa sylvatica</i> Marsh.	693	3,942	2.8	22.5	93.0	16.01
Black hickory	<i>Carya texana</i> Buckl.	408	3,937	2.8	17.8	70.9	11.01
Baldcypress	<i>Taxodium distichum</i> (L.) Rich.	221	3,695	3.3	42.8	250.2	28.44
Northern red oak	<i>Quercus rubra</i> L.	833	3,319	2.8	29.2	94.5	14.36
Winged elm	<i>Ulmus alata</i> Michx.	971	3,170	2.8	13.6	67.8	10.32
Red maple	<i>Acer rubrum</i> L.	316	3,113	2.8	16.1	89.4	12.81
Green ash	<i>Fraxinus pennsylvancia</i> Marsh.	544	3,058	2.8	28.1	96.5	17.21
Willow oak	<i>Quercus phellos</i> L.	831	2,867	2.8	37.6	149.1	20.30
Mockernut hickory	<i>Carya tomentosa</i> Poir. Nutt.	409	2,572	2.8	19.0	85.3	12.84
Sugarberry	<i>Celtis laevigata</i> Willd.	461	2,486	2.8	28.5	114.3	14.92
Eastern redcedar	<i>Juniperus virginiana</i> L.	68	2,435	2.8	15.2	72.9	9.57
Blackjack oak	<i>Quercus marilandica</i> Muenchh.	824	2,304	2.8	20.4	72.1	11.35
Cherrybark oak	<i>Quercus pagoda</i> Raf.	813	2,112	2.8	37.7	117.3	20.22
Water tupelo	<i>Nyssa aquatica</i> L.	691	2,061	2.8	31.5	95.5	13.09
Overcup oak	<i>Quercus lyrata</i> Walt.	822	2,010	2.8	40.4	129.8	19.92
American elm	<i>Ulmus americana</i> L.	972	1,734	2.8	24.3	148.6	18.28
American hornbeam	<i>Carpinus caroliniana</i> Walt.	391	1,271	2.8	11.8	44.5	7.53

hundreds to thousands of individual growth measurements are first evaluated to produce the final set of high-performing trees. In fact, PRI models must be derived from extensive inventories if the methodology is to remain ecologically and statistically robust (Bragg 2001a, in press a).

CHALLENGES TO THE APPLICATION OF INVENTORY INFORMATION

As can be seen in the preceding paragraphs, every growth model comes with potential and challenges, not the least of which is user confidence. Ecological modelers are often leery of purely empirical designs because of their less than satisfactory mechanisms, yet many also find mathematical or process approaches troubling because of shortcomings in

their structure and implementation. New techniques like PRI that blend empirical, mathematical, and process-based principles have considerable promise in the development of optimal growth equations because of their flexibility and robustness. However, as with any system derived from inventory data, the PRI methodology has two areas of concern (missing data and outlier handling) that need to be addressed further.

Missing Data

Regardless of how accurately measurements are taken, errors of omission can be problematic for optimal increment models (Bragg 2001a). Fortunately, while the PRI methodology is sensitive to limited data, the process is designed to

conservatively estimate potential increment (Bragg 2001a). Regression models can also suffer from inadequate interpolation or inappropriate extrapolation (Vancly 1994) due to missing or limited data. Problems may also arise if certain environmental conditions are absent from the inventory (e.g., no wet bottomlands or steep, rocky slopes), so as much of the expected range of site conditions as possible should be included to promote model applicability. Narrow sampling conditions can still be projected, so long as it is recognized that the resulting models should not be extrapolated to other environments.

Much of this challenge can be addressed by broadening the sampling extent. For instance, Bragg and Guldin (in preparation) considered the role of regional distribution and sample size on PRI models for white oak in the Interior Highlands of Arkansas, Missouri, and Oklahoma. Pronounced differences in white oak performance appeared in regional PRI models, primarily due to limited representation in critical size classes rather than insufficient total sample size (fig. 4). Fortunately, we found that pooling the regional models ameliorated differences and improved model outcome. Bragg (2001a) recommends at least 100 trees per species before developing PRI equations, but even this sample size may be inadequate, especially for widely

distributed taxa. Missing species, diameters, or site conditions could be addressed by strategically supplementing the inventory with additional field sampling or the incorporation of other data sets.

Outlier Handling

Every inventory-based optimal diameter increment model needs to address outlier handling because even the best implemented system will have some records that dramatically differ from the rest of the data. In most cases, either a measurement or a transcription error slipped undetected through quality control. However, it is possible that some presumed outliers may actually represent growth at a heretofore unobserved rate and thus reflect the true potential. To date, the PRI outlier strategy has been to simply delete points that noticeably depart from other data (figs. 3a and 3b). This has worked well, because few species have more than one or two obviously errant points. For example, Bragg (in press a) was able to easily identify an outlier in an Arkansas loblolly pine EFIDB data set because the large loblolly averaged 4.2 cm of growth annually for 7.2 years (i.e., during this period, it increased from 61 to 90 cm d.b.h.).

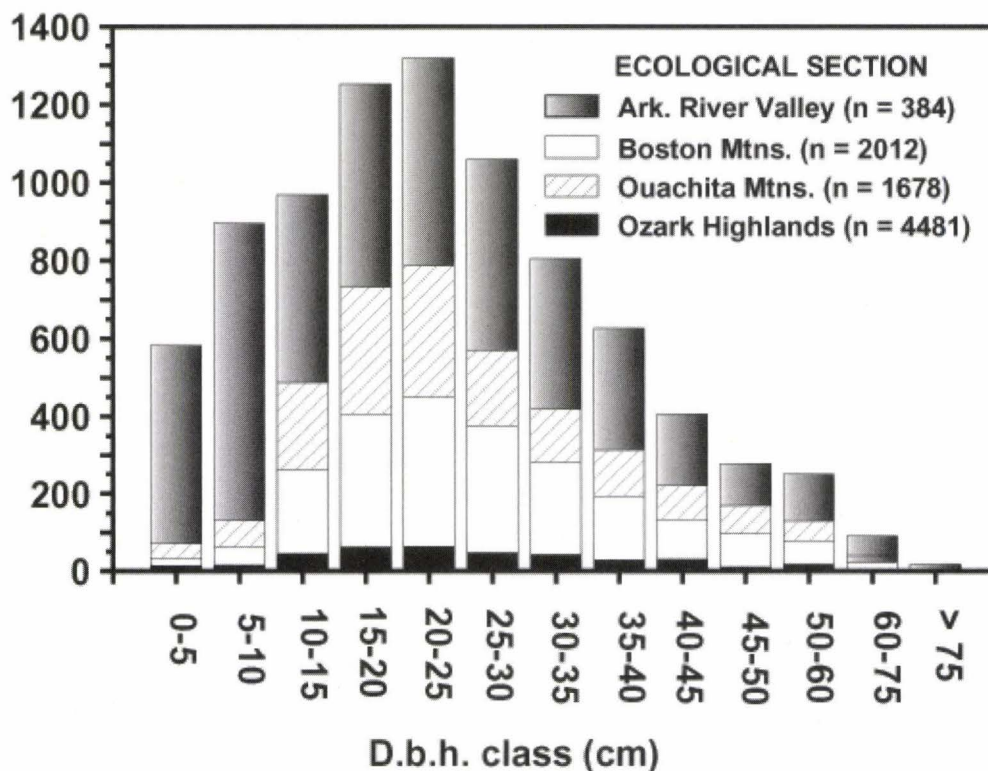


Figure 4.—White oak sample distribution from the Interior Highlands ecoregion of Arkansas, Missouri, and Oklahoma (adapted from Bragg and Guldin (in preparation)). Ecological section PRI sample sizes were unevenly distributed, both geographically and statistically.

But what happens with data points that do not deviate appreciably from the “good” data? Is there a better way to fit equations to incorporate more of the information otherwise excluded via the PRI methodology? These questions invariably arise when hundreds or thousands of data points are discarded when the final subset is chosen. Bragg (in preparation b) suggested the possibility of using a top-averaging design in which a fixed number (or percent) of the fast growing records per size class are averaged and then fitted. While a top-averaging approach increases the information content of the equations, it results in optimal growth equations that are even more conservative than the PRI models. Other statistical approaches like quantile regression have been used to identify curves corresponding to various quantiles (e.g., Koenker and Bassett 1978, Yu and Jones 1998). While these have fit splines rather than specific functions like PRI, they could identify different thresholds of acceptance based on predetermined criteria (e.g., optimal increment curves developed using the 95th quantile).

EFFICACY OF INVENTORY DATA

Inventories provide the opportunity to “model from the extremes” (Zeide 1991) and to develop optimal tree increment models based strongly in ecological theory and statistical robustness. Unfortunately, many ecologists have avoided using inventories to develop increment models because they are not aware of their availability or do not appreciate the usefulness of these data. Other growth and yield researchers have not grasped the opportunity to craft alternative approaches to forecasting increment potential. For example, Lessard and others (2001, p. 302) dismissed the value of potential growth models for projecting FIA plots into the future because “...potential growth cannot be observed and historical procedures for estimating it are complex and time consuming.” While it is essentially true that potential growth cannot be measured directly, it can be estimated with relatively simple and quick techniques (Bragg 2001a, in press b).

CONCLUSIONS

Inventories have considerable potential to contribute to the development of empirically based, ecologically valid, and statistically robust optimal tree diameter increment models. To ensure the optimal increment models developed from inventory data reasonably approximate species potential,

steps can be taken to increase model reliability. The most salient points include the application of accepted ecological theory, robust yet economic statistical derivation, flexibility and generality in model design, and use of reliable inventory information. Providentially, blending the important biological and statistical properties markedly improves the development and application of increment models. While some notable challenges remain, the PRI methodology is a good example of how these desirable aspects can be incorporated with existing inventories to develop models of potential growth.

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DEVELOPING THE NEXT GENERATION OF FOREST ECOSYSTEM MODELS

Christopher R. Schwalm and Alan R. Ek¹

ABSTRACT.—Forest ecology and management are model-rich areas for research. Models are often cast as either empirical or mechanistic. With evolving climate change, hybrid models gain new relevance because of their ability to integrate existing mechanistic knowledge with empiricism based on causal thinking. The utility of hybrid platforms results in the combination of mensurational and physiological outputs and model routines. We present model precepts for constructing a hybrid model able to accommodate climate change and schematic examples of hybrid submodules for biomass to dimension conversion, light interception, photosynthesis, and soil water.

Forest growth and change models have a long and rich history of development. For example, Kickert and others (1999) discussed approximately 125 predictive models of all types in the context of global climate change. The Register of Ecological Models, a Web-based meta-database maintained at the University of Kassel, Germany (<http://eco.wiz.uni-kassel.de/ecobas.html>), indexes 632 models, both empirical and mechanistic, used in forestry, agroforestry, and agriculture. Similarly, Leary (1989) discussed nine unique frameworks used to model the growth of a single tree species, red pine (*Pinus resinosa*), in the Great Lakes region of the United States. The development of modeling frameworks in forestry has been encouraged by the need to combine complex biological information (Johnsen and others 2001), particularly in the context of evolving climate change (Goudriaan and others 1999). A steady increase in computing power and software has supported this trend by providing the tools for sophisticated model construction. Furthermore, the investment in modeling efforts underscores the importance of numerical, predicative models as tools to evaluate the effect of anthropogenic climate change on forest ecosystems (Friend and others 1997).

Despite this proliferation of models, climate change is not adequately accommodated in the current generation of forest growth simulators. Shortcomings concern model construction (Clark and others 2001) and climate change

response potential (Schwalm and Ek 2001). Similarly, the dichotomy of empirical versus mechanistic models is also a shortcoming. The former issue is treated in Kickert and others (1999), Kley and others (1999), and Schwalm and Ek (2001). This paper concentrates on model design that bridges the gap between empirical and mechanistic methods in the context of individual tree level models. Specifically, the paper has the following objectives: (i) to establish the relevance of a hybrid modeling philosophy, (ii) to offer design precepts that allow the construction of an individual tree growth simulator responsive to the boundary conditions that define anthropogenic climate change, and (iii) to present a schematic discussion of hybrid submodules to demonstrate the utility of the approach.

THE RELEVANCE OF A HYBRID MODEL

Before design precepts are discussed in general, the relevance of a modeling framework based on both empirical and mechanistic methods, a hybrid model, must be established. The concept includes not only improving the utility of empirical models, but also improving primarily mechanistic models (Mäkelä and others 2000). Ultimately, this relevance is grounded in improved model flexibility and utility and the inability of solely empirical frameworks to accommodate climate change.

Climate Change

Solely empirical frameworks are incapable of accommodating climate change. By definition, climate change encompasses a

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change in boundary conditions that govern tree growth (sensu Kellomäki and Väisänen 1997). Mechanistic models use parameters with biological interpretability, and models are driven by the very boundary conditions that climate change will modify. On the other hand, empirical models use coefficients as generated by some notion of statistical fit devoid of causal thinking. Consequently, such parameters encapsulate the effect of past climate on tree growth without any formal link to climatological variables (Korzukhin and others 1996, Mäkelä and others 2000). Thus, the climatic information embedded in a calibration data set used to generate coefficients (e.g., Forest Vegetation Simulator: Van Dyck 2001) has become outdated and obsolete and cannot be expected to accurately predict climate change.

Changing Currencies

Assuming that the ecological and physiological interdependencies between tree growth and tree environment have been properly specified and parameterized, another failing of the current crop of forest growth models is their inability to interface with operational considerations (cf. Johnsen and others 2001). Mechanistic modeling logic is ultimately in terms of kilograms of dry matter (e.g., C_3 biochemical model of assimilation developed by Farquhar and co-workers [De Pury and Farquhar 1997, Farquhar and others 1980]). Nonetheless, characterizing the structure of a given forest requires more than the amount of biomass in each tree compartment. Forest structure (e.g., diameter class distribution) requires dimension. It follows that a forest growth simulator must offer a means to change from the currency of mechanistic algorithms (kilograms of dry matter) to dimension (feet or meters). Additionally, the overall utility of a modeling framework would be enhanced by provision for mensurational as well as physiological output.

A corollary of this results in a model design where typical forest inventory data can be used to initialize a mechanistic model. Typically, field plot data are based on classic mensurational observations concerned with the physical dimension of individual trees rather than kilograms of dry matter. As such, the need for switching between physical dimensions and kilograms of dry matter is omnipresent. Mechanistic models require that a tree be compartmentalized into various component pools of carbon for initialization. However, an accurate determination of plant carbon distribution is impossible without destroying the specimen. This forces the use of allometric relationships (e.g., Ter-Mikaelian and Korzukhin 1997).

Silvicultural Prescriptions

Operational models typically simulate the effects of silvicultural manipulations (e.g., Forest Vegetation Simulator: Van Dyck 2001). However, the current dichotomy between empirical models and mechanistic models is such that the latter rarely provide for silviculture prescriptions. In other words, thinnings are realized by some function of traditional mensurational variables (e.g., diameter at breast height). When a model is designed to be used both in an operational as well as a research context, a net gain results in terms of model utility. The framework is driven by a mechanistic growth engine but is also amenable to the vast amount of thinning algorithms that require dimension.

Knowledge Gaps

To design a model able to accommodate climate change requires that the same model be based on process where possible. However, mechanistic modeling logic is not an end to itself. The inclusion of unified, physiology based formulations is obvious when they exist (e.g., photosynthesis: De Pury and Farquhar 1997, Farquhar and others 1980). In the case of gross and net productivity, carbon allocation and competition, regeneration and mortality (Mäkelä and others 2000 and references within), and stomatal conductance (Campbell and Norman 1998), such unified mathematical treatments do not exist. In the absence of such algorithms, robust and/or climate-driven empirical relationships are required, e.g., stomatal conductance as modeled via reduction factors (Chen and others 1999) or soil water holding capacity as a function of texture (Cosby and others 1984, Kimball and others 1997). This has the advantage of reducing the number of parameters needed for model initialization as well as incorporating existing, albeit descriptive, knowledge of a particular process.

In the end, a hybrid model serves to join mechanistic and empirical philosophies to offset a lack of knowledge of key physiological processes. Simultaneously, the range of applicability of the model itself is enhanced by allowing an interface with silvicultural routines and traditional mensurational output. A reduction in the number of parameters needed is also realized by using empiricism in controlled instances.

DESIGN PRECEPTS

The modeling approach suggested here addresses the lack of an individual tree level model driven by climate and responsive to changing boundary conditions (i.e., climate change). The design philosophy is based on two principles. First, the environmental drivers that influence forest growth in nature must be the same as those that drive model output. As much as possible, the driving variables of the model are climatic (*sensu* climate change), including ambient concentration of relevant gases (e.g., CO₂ and O₃) (Bossel 1991, 1996). The goal is to obviate, as much as possible, the need for model calibration and to generate model outputs that are devoid of predetermined statistical relationships (Friend and others 1997). Second, models should be accessible to both operational forest management professionals and researchers. The net result is a modeling framework that is hybrid in nature. Empirical relationships are used to effect thinnings, produce mensurational output, and initialize the model (i.e., field plot data). Furthermore, physiological processes are replaced with robust, climate-driven empirical relationships where mechanistic algorithms are yet undeveloped or require infeasible parameterizations (Mäkelä and others 2000).

In sum, the design philosophy aims to bridge the gap between empirical models and mechanistic models (Korzukhin and others 1996, Mäkelä and others 2000) and to accommodate climate change while requiring only basic meteorological and forest inventory data for initialization. The issue of model resolution or scale, both temporal and spatial, is of prime importance. Its interplay with physiology results in different model formulations of the same underlying process across temporal and spatial gradients (e.g., transpiration: Jarvis and McNaughton 1986, photosynthesis: Chen and others 1999). We assume that the tree is the fundamental unit of prediction with ecophysiological processes, e.g., photosynthesis and transpiration, modeled for a specific tree. In other words, as the simulation progresses, tree-level attributes are updated whereas stand-level attributes emerge (i.e., emergent properties). A daily time step is used to capture seasonal variation in accordance with available meteorological data (Waring and Running 1998) with diurnal variation subsumed into relevant algorithms or accounted for using idealized daily patterns (e.g., the use of sine functions to characterize radiation loads over the course of a day).

MODEL CONSTRUCTION

Constructing a model that incorporates the above specified design philosophy is challenging. Various realizations are possible, depending upon the ultimate use of the model. To illustrate, four submodules will be discussed that incorporate this philosophy: biomass to dimension, light interception, photosynthesis, and hydrology.

Biomass to Dimension

A hybrid model can be thought of as a mechanistic growth engine sandwiched between biomass equations. The modeling framework must provide a means to convert from dimension to dry matter mass. This is typically accomplished using empirical relationships based on tree allometry and the pipe model theory (i.e., physio-allometric relationships: Mäkelä 1997). At the beginning of each simulation, dimension is converted to biomass to initialize various carbon pools as dictated by the model's structure. This includes the conversion of foliage mass to leaf area via specific leaf area values and ultimately leaf area index (Waring and Running 1998). When biomass is to be converted to dimension—for example, in the context of report writing—the same equations are used in reverse, i.e., by switching explanatory and response variables. Statistically speaking, transforming such equations is not without compromise. However, we have been unable to find biomass equations that compute dimension from compartment biomass.

Light Interception

Modeling light interception is a less trivial exercise. Several approaches are seen in forestry modeling. These range from multilayered three dimensional treatments where each tree crown has an idealized geometric shape (e.g., Stand-BGC: Milner and Coble 1995; Hybrid v3.0: Friend and others 1997) to so-called “big leaf” models where the canopy is mathematically defined as a single photosynthetic surface (e.g., Biome-BGC: Kimball and others 1997; Forest 5: Robinson 1998). Superimposed on the issue of spatiality is the partitioning of diffuse and direct beam light and their relationships to sunlit and shaded leaf irradiance. The differential response of sunlit and shaded leaves to increased CO₂ (Ågren and others 1991, Campbell and Norman 1998, Goulden and others 1997) highlights the importance of partitioning leaf area as well.

An approach that incorporates the above considerations is based on the relationship between diurnal temperature range and ambient temperature as discovered by Bristow and Campbell (1984) and refined by Thornton and Running (1999). Here, daily total transmittance (T_t) is calculated as a function of common meteorological variables, sun-earth geometry, the solar constant, and rainfall. T_t is then used to attenuate the solar constant through the atmosphere. Radiation is partitioned according to an empirical function of daily total transmittance (Gates 1980, Thornton and others 2000). Irradiance on sunlit and shaded leaves (Norman 1982) is then a function of direct beam versus diffuse light, foliage clumping indices (corrected for crown ratio), zenith angle at solar noon, and leaf area index in both shaded and sunlit. The only parameters required are those concerning foliage clumping indices, and these can be readily gleaned from the literature (e.g., Campbell and Norman 1998, Chen 1996, Chen and others 1997).

Photosynthesis

A natural choice for mechanistic models is the Farquhar C_3 model of biochemical assimilation (De Pury and Farquhar 1997, Farquhar and others 1980). Although Farquhar's model was originally developed for instantaneous net assimilation at the leaf level (Farquhar and others 1980), it has been scaled temporally and with curvature corrections (cf. Kellomäki and Väisänen 1997). Chen and others (1999) integrated Farquhar's original model over a day while incorporating sunlit and shaded components of photosynthesis as specified above. This assumes idealized leaf geometry, diurnal patterns in radiation, temperature, and photosynthesis that enable integration with respect to stomatal conductance. Stomatal conductance is a function of a maximum theoretical value and common meteorological variables embedded in modifiers. Net daily assimilation is then a function of well-defined parameters readily available in the literature, daily temperature, precipitation, stomatal conductance, ambient CO_2 and O_3 , and soil water potential. Site nutrient status, via foliar nitrogen, can also be incorporated if desired.

Hydrology

Given the heterogeneity of the soil resource, a portable mathematical description of soil hydrology is difficult to realize (Johnsen and others 2001). Mechanistic soil

hydrology models typically require detailed knowledge of the pedon and extensive parameterizations, often involving processes seldom measured (e.g., NuCM: EPRI 1993; ACIDIC: Kareinen and others 1998). A mechanistic treatment of water dynamics is often impractical. An approach that dovetails with the above submodules is that used in Biome-BGC (Kimball and others 1997) and Stand-BGC (Milner and Coble 1995). The BGC approach is based on statistical relationships formulated by Cosby and others (1984) with regression equations used to determine soil water potential based on soil texture. All intermediate quantities such as volumetric water at saturation are functions of soil texture as well. Plant available water in totality is a function of soil texture, rooting depth, and precipitation. Total plant available water is abstracted into a water bucket with the amount of water available to a particular tree linked to the ratio of tree leaf area to site total leaf area.

Data Requirements

Based on the schematic discussion of the submodules, the overall data requirements are modest: (i) field plot data: diameter at breast height, total height, crown ratio, and species; (ii) weather station data: daily precipitation and daily temperature, ambient CO_2 and O_3 concentrations; and (iii) other: latitude, Julian day, solar constant, elevation. Alternatively speaking, the result of the aggregation of processes concomitant in the construction of a hybrid model and the application of the design tenants is a series of submodules that require little in the way of initialization.

DISCUSSION

The advantages of hybrid modeling are clear: (i) mensurational and physiological output; (ii) access to empirical treatments of thinning, mortality, and regeneration; (iii) modest data requirements, i.e., model initialization based on typical field plot data; (iv) a decrease in the number of required model parameters; and (v) a means to overcome lack of mechanistic knowledge through empiricism based on causal thinking. Also, using empirical knowledge does not, by definition, prevent a treatment of climate change. In each of the above submodules, all empirical relations use climate-related explanatory variables. This is more than an attempt to maximize some notion of statistical fit; rather it is an attempt to incorporate a degree of causality into such relationships (Korzukhin and others 1996, Mäkelä and others 2000).

Despite these advantages, hybrid modeling endeavors are scant. Friend and others (1997) developed a hybrid model, Hybrid v3.0, for the United Kingdom based on functional groups as the terrestrial component of a whole system hierarchy of models. Milner and others (2002) linked the Forest Vegetation Simulator, Inland Empire version (Wykoff and others 1982), with Stand-BGC (Milner and Coble 1995), an individual tree level version of the BGC logic (Waring and Running 1998) to provide the latter with a mechanistic engine. Similarly, Baldwin and others (1998) linked PTAEDA (Daniels and Burkhardt 1975), a distance-dependant growth and yield model, and MAESTRO (Wang and Jarvis 1990), a canopy-level mechanistic treatment of photosynthesis, to better estimate stand carbon gain and to investigate climate change scenarios. Baldwin and others (2001) then combined MAESTRO with an updated version of PTAEDA to predict changes in site quality (i.e., site index) based on physiological (e.g., photosynthesis) and mensurational (e.g., tree per area) variables. Ågren and Bosatta (1988) analyzed nutrient cycling in forested ecosystems using empirical plant growth routines and mechanistic soil carbon algorithms. The individual tree model Forest v5.1, under development at the University of Minnesota, combines the above submodules to predict the tree carbon budget under climate change while allowing for silvicultural manipulation (Robinson 1998).

Viewed in their totality, such modeling endeavors highlight the potential gains from hybrid modeling. As knowledge increases and biologically defensible parameterizations of key physiological processes become a reality, hybrid modeling will likely become less attractive. Nonetheless, the ability of hybrid modeling philosophies to bridge gaps in knowledge and to produce diverse outputs should ensure their use in the foreseeable future.

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IMPLEMENTING A LAND COVER STRATIFICATION ON-THE-FLY

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ABSTRACT.—Stratified estimation is used by the Forest Inventory and Analysis program of the USDA Forest Service to increase the precision of county-level inventory estimates. Stratified estimation requires that plots be assigned to strata and that proportions of land area in each strata be determined. Classified satellite imagery has been found to be an efficient and effective means of accomplishing both tasks. This study investigated methods for making the county stratifications available for use with user-defined areas without storing the entire pixel-level stratification and processing it separately for each application. Summaries of stratifications at spatial scales of 6,000 acres and less produced stratified estimates at county level and for user-defined areas ranging in size from approximately 300 square miles to approximately 8,000 square miles that were very similar to stratified estimates obtained using the underlying pixel-level stratifications.

The Forest Inventory and Analysis (FIA) program of the USDA Forest Service reports county-level estimates of the means and standard errors for forest land area and live tree volume per unit area for each state. Budgetary constraints and the natural variability among plots prohibit sample sizes sufficient to satisfy national precision standards (USDA-FS 1970) unless the estimation process is enhanced using ancillary data. The FIA program enhances the process using stratified estimation with counties stratified using remotely sensed data. Stratified estimation requires that two tasks be accomplished: each observational unit must be assigned to a stratum, and strata weights must be calculated as the proportions of the area of interest in strata. When satellite imagery is used as the means of stratification, observational units are assigned to strata on the basis of the strata assignments of their associated satellite image pixels, and strata weights are calculated as the proportions of image pixels assigned to strata.

Both FIA and non-FIA users frequently require estimates of inventory variables for areas other than counties, and if the FIA county-level stratifications can be used, the precision of

estimates for these user-defined areas will be increased. If storage space and processing time were not constraints, the FIA database (FIADB) (Miles and others 2001) would provide access to FIA's pixel-level strata assignments so that users could stratify their areas of interest in the same manner as FIA stratifies counties. However, because storage space and processing time are constraints, this approach is not feasible at the current time. Therefore, the FIA program seeks methods for summarizing county stratifications and making them available to users without the intense storage and processing requirements.

The objective of this study is to compare stratified estimates obtained using pixel-level stratifications with estimates obtained using summaries of pixel-level stratifications. The comparisons focus on estimates of plot-level means and standard errors for proportion forest land area and volume per unit area using 1998 FIA data for the state of Indiana. Among the observations field crews obtain when measuring plots are individual tree diameters and heights and the proportions of plot areas that satisfy specific ground land use conditions. The tree diameter and height observations are used as predictor variables to obtain model predictions of individual tree volumes. Plot-level volume is obtained by adding the volume predictions over all trees and scaling the sum to a per unit area basis. Plot-level forest land proportions are obtained by aggregating ground land use conditions consistent with the FIA definition of forest land.

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STRATIFIED ESTIMATION

The National Land Cover Data (NLCD) is a satellite image-based classification that has been used by the FIA program as a basis for stratifications. The NLCD, a digital product of the Multi-Resolution Land Characterization (MRLC) Consortium (Loveland and Shaw 1996), is a land cover map of the conterminous United States consisting of assignment of each 30 m x 30 m pixel to one of 21 land cover classes. The land cover classification was produced by the U.S. Geological Survey and is based on nominal 1992 Landsat 5 Thematic Mapper (TM) satellite imagery and a variety of ancillary data. Vogelmann and others (2001) provide an excellent overview and discussion of the NLCD.

FIA obtains stratifications from the NLCD using a three-step process. First, NLCD classes 33 (transitional)², 41 (deciduous forest), 42 (evergreen forest), 43 (mixed forest), 51 (shrubland), and 91 (woody wetland) are aggregated into a forest stratum, and the remaining classes are aggregated into a nonforest stratum. Second, a clumping and sieving algorithm (ERDAS 1997) is used to reassign isolated groups of small numbers of contiguous forest pixels to the nonforest stratum and isolated groups of small numbers of contiguous nonforest pixels to the forest stratum. Groups of less than 4 pixels are reassigned because of the approximate correspondence of their aggregated area of 38,750 ft² to 1 acre, the minimum area necessary to be designated FIA forest land. Third, two additional strata are created by subdividing the forest stratum into forest and forest edge strata and by subdividing the nonforest stratum into nonforest and nonforest edge strata (Hansen and Wendt 2000, McRoberts and others 2001). These edge strata are created by assigning pixels in the original forest stratum within 2 pixels of the forest/nonforest boundary to a forest edge stratum and by assigning pixels in the original nonforest stratum within 2 pixels of the forest/nonforest boundary to a nonforest edge stratum.

The rationale for creating the edge strata is based on the knowledge that stratification contributes to increasing precision under two conditions: when within-stratum variances are smaller than the overall variance, and/or when

strata with large variances represent relatively small proportions of the total population. Plots located in the interior of the forest stratum and away from forest/nonforest boundaries are expected to be predominantly forest, while plots located in the nonforest stratum away from the forest/nonforest boundaries are expected to be predominantly nonforest. In both cases, within-stratum variances are expected to be relatively small, thus satisfying the first condition for which stratification increases precision. Plots located in an edge stratum, i.e., near forest/nonforest boundaries, are expected to exhibit greater variances due to a mix of forest and nonforest conditions and due to the greater probability of errors in assigning plots to strata as a result of plot location errors. Nevertheless, the stratification is expected to concentrate these mixed forest/nonforest and erroneously stratified plots into strata that represent relatively small proportions of the total area, thus satisfying the second condition for which stratification produces increases in precision.

The FIA program assigns plots rather than subplots to strata to avoid the mathematical complexities necessary to accommodate the correlations among subplot observations. Nevertheless, assigning FIA plots to strata may not be trivial, because each plot is covered by multiple TM pixels. For the sake of simplicity, each plot is assigned to the stratum of the pixel corresponding to the plot center for this study. Strata weights are then calculated as the proportions by strata of pixels with centers in the county. For future reference, this stratification method is designated the pixel method and is the standard of comparison for other methods.

Stratified estimates of means and variances means are obtained using formulae from Cochran (1977)

$$\bar{x}_{\text{str}} = \sum_{h=1}^H w_h \bar{x}_h \quad (1)$$

and

$$\text{Var}(\bar{x}_{\text{str}}) = \sum_{h=1}^H w_h^2 \frac{\hat{\sigma}_h^2}{n_h} \quad (2)$$

where

$$\bar{x}_h = \sum_{k=1}^{n_h} x_{hk} \quad (3)$$

$$\hat{\sigma}_h^2 = \frac{\sum_{k=1}^{n_h} (x_{hk} - \bar{x}_h)^2}{n_h - 1} \quad (4)$$

² The correct numerical designation for the transitional class is 33; its designation as 31 in Vogelmann and others (2001) is attributed to a manuscript error (Vogelmann, EROS Data Center, U.S. Geological Survey, personal communication, 10 October 2001).

$\bar{x}_{str}$ denotes the stratified mean, $h=1, \dots, H$ denote strata, w_h denotes the h^{th} stratum weight, n_h denotes the number of plots assigned to the h^{th} stratum, $k=1, \dots, n_h$ indexes observations within the h^{th} stratum, $\bar{x}_h$ denotes the mean for the h^{th} stratum, and $\hat{\sigma}_h^2$ denotes the variance for the h^{th} stratum.

STRATIFICATION SUMMARIES

The traditional FIA approach to summarizing county-level stratifications is via area expansion factors. For the h^{th} stratum in the c^{th} county, the area expansion factor, F_{ch} , is calculated as,

$$F_{ch} = \frac{A w_{ch}}{n_{ch}} \quad (5)$$

where A is the total county area and w_{ch} and n_{ch} are the stratum weight and the number of plots, respectively, for the h^{th} stratum in the c^{th} county. F_{ch} expresses the land area in the c^{th} county represented by each plot in the h^{th} stratum and is assigned to all plots in that county-stratum combination. The area expansion factors provide a crude summary of county stratifications. However, it is not necessarily the case that $F_{c'h} = F_{c''h}$ where c' and c'' designate different counties. To calculate stratified estimates using area expansion factors, strata assignments of plots from the county stratification are used, and strata weights are estimated as ratios of the sum of area expansion factors for all plots assigned to strata and the sum of area expansion factors for all plots over all strata. Within-strata means and variances are calculated using (4) and (5) except that each plot observation is weighted by the appropriate F_{ch} . This method for summarizing a stratification is designated the area expansion factor method.

Stratifications may also be summarized by counting and storing the numbers of pixels by strata for summary units at a variety of spatial scales. For example, beginning with an arbitrarily selected starting point, the State of Indiana was covered by a set of non-overlapping square kilometers, the numbers of pixels with centers in each square kilometer were counted by strata, and the strata pixel counts for each square kilometer were stored for future use. This method for summarizing a stratification is designated the square kilometer method.

The FIA sampling design is based on an array of regular hexagons covering the conterminous United States. Each hexagon includes 5,937.2 ac and contains at least one

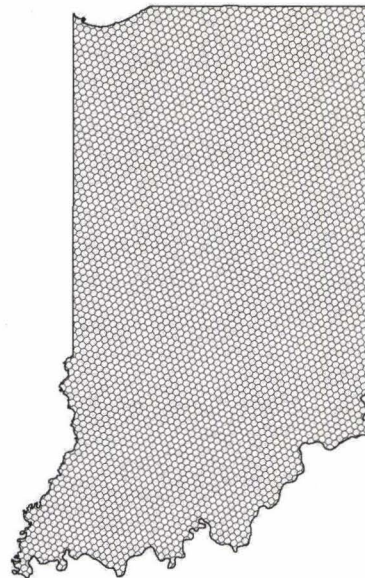


Figure 1.—Indiana FIA hexagons.

permanent field (fig. 1). This network of plots is designated the Federal base sample and provides complete, consistent coverage of all lands in the United States. To facilitate intensification of the sample for some states, the hexagons have been subdivided into three parallelograms designated subhexagons (fig. 2). Stratifications are summarized at the subhexagon and hexagon level in the same manner as for square kilometers and are designated the subhexagon and hexagon methods, respectively.

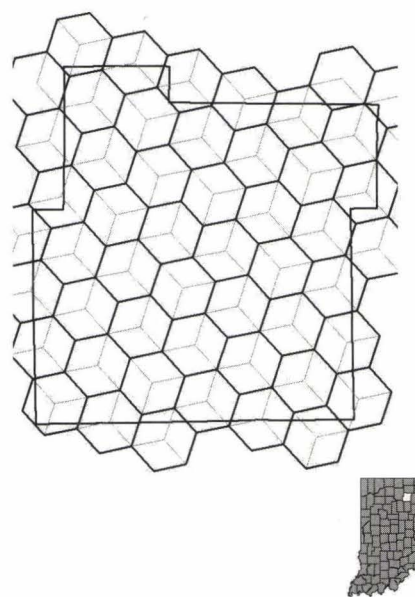


Figure 2.—FIA hexagons and sub-hexagons for Whitley County, Indiana.

STRATIFIED ESTIMATION USING STRATIFICATION SUMMARIES

To obtain stratified estimates for user-defined areas with stratification summaries, the same two stratification tasks must be accomplished: plots must be assigned to strata, and strata weights must be calculated. The first task is easily accomplished by using the same strata assignments as for the county stratifications. Several approaches may be used to accomplish the second task. One approach is to select the summary units with centers in the user-defined area, add the pixel counts by strata over these units, and calculate strata weights as the proportions of pixels assigned to strata. This approach, based on including or excluding a summary unit's pixel counts in the overall total on the basis of whether the center of the unit is inside the user-defined area, is designated the center approach and is used in combination with the square kilometer, subhexagon, and hexagon summary units.

The pixel counts by strata using the center approach will not be the same as those obtained using the pixel method, because the exterior boundaries of the spatially aggregated summary units will not coincide exactly with the boundaries of the user-defined area. To simplify the discussion that follows, two categories of summary units are distinguished: interior summary units are wholly within the user-defined area, while boundary summary units are only partially within the user-defined area. Boundary units cause two kinds of errors in pixel counts for a user-defined area. Boundary units with centers inside the user-defined area cause pixel counts by strata over all units to include counts for some pixels outside the user-defined area, and boundary units with centers outside the user-defined area cause pixel counts by strata over all units to exclude counts for some pixels inside the user-defined area. However, stratified estimation does not require pixel counts by strata, because strata weights are calculated as proportions of pixel counts. Thus, even though counts for some pixels are erroneously included and some are erroneously excluded in the pixel counts by strata over summary units, the strata weights may still be approximately correct.

Two additional approaches are investigated. The first additional approach includes pixel counts for boundary summary units on the basis of whether any part of the unit is inside the user-defined area. This approach is designated the exterior approach, because the boundaries of the spatially aggregated summary units coincide with or are exterior to the boundaries of the user-defined area. The exterior approach counts all pixels in boundary units, regardless of whether the unit center

is inside or outside the user-defined area. The exterior approach is used only in combination with hexagon summary units. The corresponding interior approach is not investigated because of the risk of excluding so many pixels that the counts by strata will not accurately represent the user-defined area. This risk is particularly problematic for user-defined areas with narrow components for which the ratio of interior boundary units to boundary summary units is small.

The second additional approach attempts to compensate for pixel inclusion and exclusion errors. With this approach, the pixel counts by strata for boundary summary units are adjusted by multiplying them by the proportion of the unit in the user-defined area. The additional computation necessary to determine the proportion for each boundary unit may produce more accurate pixel counts and hence more accurate strata weights. This approach is designated the proportional approach. Care should be taken to distinguish the proportional approach from an approach that obtains pixel counts by strata for boundary units by first determining the portion of the unit in the user-defined area and then counting only pixels in the selected portion. Although this is exactly the approach that would be used under ideal conditions, it is also exactly the storage- and processing-intensive approach for which this study seeks alternatives. The proportional approach is used only in combination with hexagon summary units.

ANALYSES

Two sets of analyses are used to compare stratified estimates obtained using the pixel stratification method with estimates obtained using stratification summary methods. For both sets of analyses, the comparisons focus on estimates of plot-level means and standard errors for proportion forest land area and volume per unit area in Indiana. The purpose of the first set of analyses is to evaluate the bias in the stratified mean and standard error estimates that result from summarizing stratifications using the square kilometer, subhexagon, and three hexagon methods. Bias was evaluated using the distributions over the 92 Indiana counties of three statistics: (1) the relative bias, calculated as the ratio of the difference in means for the pixel method and each of the summarization methods and the mean for the pixel method; (2) the t-statistic, calculated as the ratio of the difference in means for the pixel method and each of the summary methods and the standard error of the mean for the pixel method; and (3) the ratio of relative efficiencies for the pixel method and each of the summary methods where relative efficiency is the ratio of the variance of the mean assuming simple random sampling and

the variance obtained using stratified estimation. The area expansion factor method was not used for these analyses, because it produces the same estimates for counties as does the pixel method.

The second set of analyses compares methods for areas enclosed in two sets of concentric circles of radii 10, 20, 30,

40, and 50 mi. One set is centered in a sparsely forested area in northern Indiana, while the other is centered in a more heavily forested area in southern Indiana that includes the Hoosier National Forest (fig. 3). The purpose of this set of analyses is to compare estimates of the means and standard errors for areas that mimic user-defined areas. Circular areas of radius 10 miles include 314.2 mi², and with a sampling intensity of one plot for

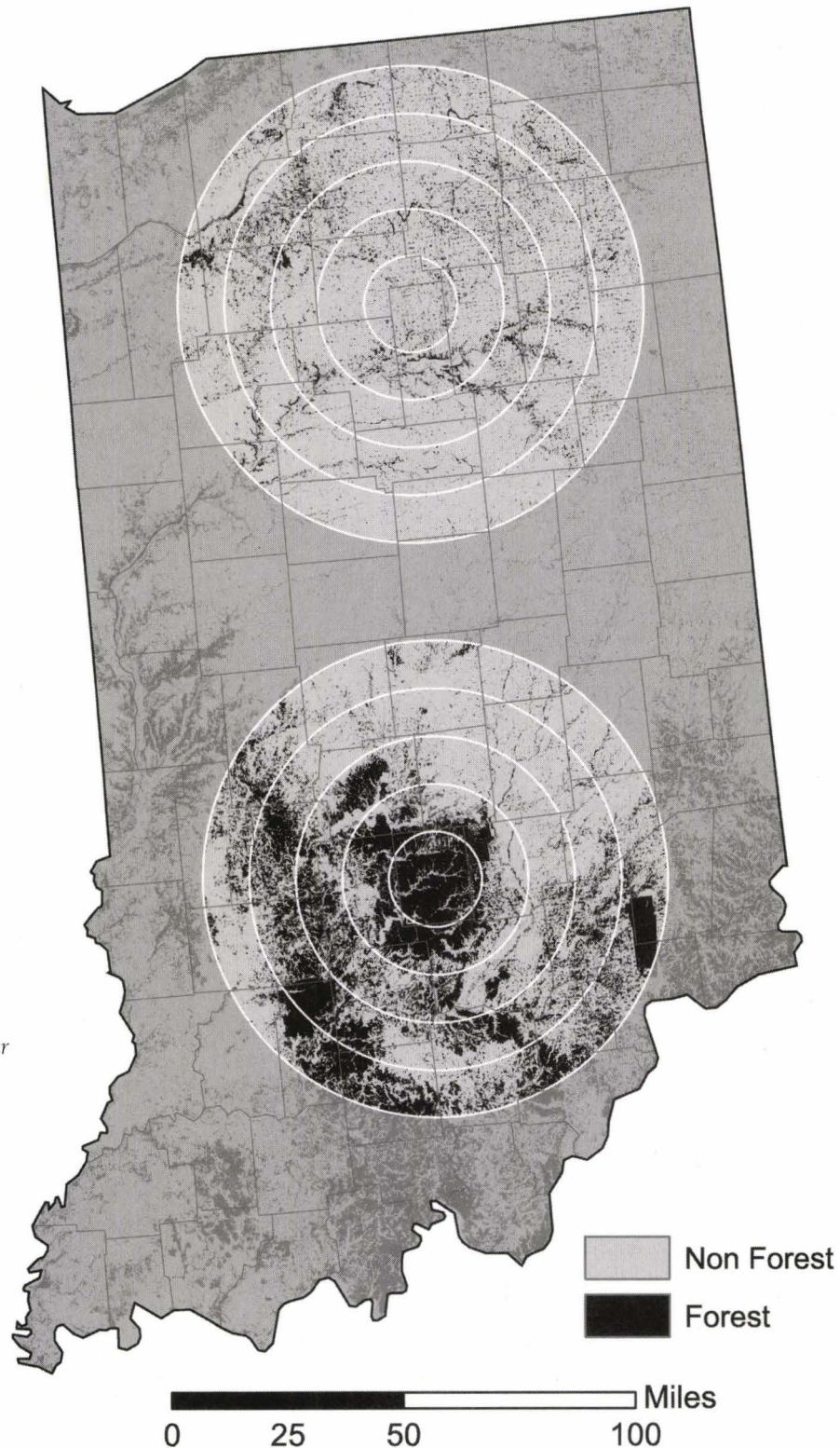


Figure 3.—User-defined circular areas for Indiana.

approximately every 5,937.2 ac, are expected to include approximately 34 plots. Assuming moderate variability in the number of plots per stratum, circular areas of radius 10 mi are about the smallest areas that ensure five plots per stratum, the FIA minimum.

RESULTS

The first set of analyses indicate that bias for the square kilometer, subhexagon, and three hexagon methods is minimal (tables 1a and 1b). As expected, bias is less for methods that

Table 1a.—Volume per unit area results over the 92 Indiana counties

Statistic	km ²	Subhexagon	Method center	Hexagon proportional	Exterior
Relative bias					
Maximum	0.017	0.028	0.058	0.084	0.291
Mean	0.000	-0.002	-0.005	-0.002	0.016
Minimum	-0.019	-0.0036	-0.083	-0.081	-0.126
t-statistic					
Maximum	0.049	0.150	0.227	0.239	1.258
Mean	-0.002	-0.010	-0.027	-0.015	0.037
Minimum	-0.088	-0.141	-0.367	-0.386	-1.071
Relative efficiency					
Maximum	1.039	1.079	1.170	1.179	1.314
Mean	0.990	0.993	0.997	0.995	0.980
Minimum	0.960	0.945	0.886	0.844	0.606

Table 1b.—Proportion forest land area results over the 92 Indiana counties

Statistic	km ²	Subhexagon	Method center	Hexagon proportional	Exterior
Relative bias					
Maximum	0.012	0.030	0.058	0.059	0.276
Mean	0.000	-0.002	-0.005	-0.002	0.016
Minimum	-0.019	-0.0035	-0.074	-0.077	-0.121
t-statistic					
Maximum	0.152	0.191	0.250	0.361	2.152
Mean	-0.002	-0.021	-0.048	-0.026	0.074
Minimum	-0.134	-0.255	-0.590	-0.641	-1.122
Relative efficiency					
Maximum	1.039	1.070	1.143	1.159	1.261
Mean	0.990	0.994	0.995	0.995	0.985
Minimum	0.978	0.944	0.894	0.917	0.681

summarize at smaller spatial scales. Among the three approaches used with hexagon summary units, the hexagon-exterior results are clearly inferior, while results obtained with the hexagon-center and hexagon-proportional methods are similar. The distributions of t-statistics indicate that differences between means obtained using the pixel method and means obtained using the summary methods are never statistically significant ($\alpha = 0.05$). It is noted that the denominator used in calculating this t-statistic includes the standard error of the mean obtained with the pixel method only. No account is made of the uncertainty associated with the standard error obtained with the stratification summary method. If the latter were included, the t-statistics would be even less statistically significant. The ratios of relative efficiencies indicate that, on average, virtually no precision is lost with the stratification summaries. Even with the inferior hexagon-exterior method, the relative efficiencies are always ± 18 percent of the relative efficiency obtained with the pixel method. Because of its inferiority relative to the other two hexagon methods, the hexagon-exterior method is not discussed further. The hexagon-center and the hexagon-proportional methods produce similar results, but the hexagon-center method is preferable because of its less intense processing requirements. Therefore, only the square kilometer, sub-hexagon, and hexagon-center methods are further evaluated.

The second set of analyses simulated user-defined areas and yielded two important findings: first, results for the square kilometer, subhexagon, and hexagon-center summary methods are similar and are similar to results obtained with the pixel method, which is the standard of comparison; and second, results for the area expansion factor method are inferior to results obtained with all the other methods (tables 2a and 2b). Results obtained with the spatial summary methods are slightly more similar to the results with the pixel method for smaller scale summary units. For practical purposes, however, there is little to distinguish among results for these three summary methods. These similarities hold for estimates of both means and standard errors.

CONCLUSIONS

Three conclusions may be drawn from this study. First, the traditional FIA area expansion factor method should be abandoned because it is inferior to the other methods.

Second, results obtained with the square kilometer, subhexagon, and hexagon-center methods were all acceptable approximations to the results obtained with the pixel stratifications. Third, the hexagon-center is the overall preferred method: it produces highly satisfactory results relative to the standard of comparison, the pixel method; it has direct linkages to the FIA national sampling design; and it requires the least storage and processing time of all the spatial summary methods considered. The quality of results for the hexagon-center method suggests that it should be investigated in other areas with different topographies, tree species, and forest management practices.

The necessity of summarizing stratifications is a temporary phenomenon that will be alleviated as the costs of computer storage and processing decrease. Nevertheless, it is worth noting the difference in storage requirements for the underlying stratification and a summary of the stratification at the hexagon level. The storage requirement for summarizing a stratification at the hexagon level is four cells, one for each of the four stratum pixel counts. For the underlying stratification, one cell is required for each of the 26,696 30 m x 30 m TM pixels contained in a hexagon of 5,937.2 ac. The magnitude of this ratio, 26,696:4, which is also an approximation of the factor by which computer processing requirements may be reduced, cannot be ignored.

Finally, one caveat must be noted. These results are predicated on the assumption that the proportions of pixels by strata obtained using stratification summaries will be approximately the same as for the underlying pixel stratification. The degree to which this assumption is valid is expected to be directly proportional to the ratio of interior summary units to boundary summary units. Additional investigations are necessary to determine the ratio at which the assumption is no longer sufficiently valid to produce acceptable results.

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Table 2a.—Volume per unit area for Indiana circular areas

Method	Radius					
	10 mi		30 mi		50 mi	
	Mean ±	SE	Mean ±	SE	Mean ± SE	
Northern area						
Area Expansion Factor	154.8 ±	24.7	166.6 ±	17.1	160.1 ±	13.5
Pixel	159.7 ±	26.2	215.2 ±	21.4	203.0 ±	18.4
km ²	159.3 ±	26.2	215.2 ±	21.4	203.0 ±	18.4
Subhexagon	161.6 ±	26.2	214.0 ±	21.3	203.0 ±	18.4
Hexagon-center	163.4 ±	26.4	214.1 ±	21.4	203.6 ±	18.4
Southern area						
Area Expansion Factor	1,258.7 ±	172.8	741.0 ±	39.3	591.5 ±	19.9
Pixel	1,122.5 ±	241.5	767.1 ±	40.2	628.6 ±	20.8
km ²	1,122.9 ±	241.2	766.9 ±	40.2	628.8 ±	20.8
Subhexagon	1,117.9 ±	239.0	764.0 ±	40.1	629.3 ±	20.9
Hexagon-center	1,113.9 ±	243.7	768.1 ±	40.3	628.9 ±	20.8

Table 2b.—Proportion forest land for Indiana circular areas

Method	Radius					
	10 mi		30 mi		50 mi	
	Mean ±	SE	Mean ±	SE	Mean ±	SE
Northern area						
Area Expansion Factor	0.010 ±	0.022	0.089 ±	0.007	0.095 ±	0.005
Pixel	0.010 ±	0.024	0.115 ±	0.007	0.115 ±	0.005
km ²	0.010 ±	0.024	0.115 ±	0.007	0.115 ±	0.005
Subhexagon	0.010 ±	0.024	0.114 ±	0.007	0.115 ±	0.005
Hexagon-center	0.010 ±	0.025	0.114 ±	0.007	0.115 ±	0.005
Southern area						
Area Expansion Factor	0.729 ±	0.065	0.389 ±	0.014	0.319 ±	0.007
Pixel	0.708 ±	0.104	0.394 ±	0.015	0.328 ±	0.007
km ²	0.708 ±	0.103	0.394 ±	0.015	0.328 ±	0.007
Subhexagon	0.704 ±	0.102	0.392 ±	0.015	0.328 ±	0.007
Hexagon-center	0.705 ±	0.104	0.394 ±	0.015	0.328 ±	0.007

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FRAGMENTATION STATISTICS FOR FIA: DESIGNING AN APPROACH

Rachel Riemann, Andrew Lister, Michael Hoppus, and Tonya Lister¹

ABSTRACT.—The USDA Forest Inventory and Analysis (FIA) program collects data on the amount of forest, as well as on characteristics such as forest type, tree volume, species composition, and size and age classes. However, little data are obtained nationwide on forest fragmentation—how that forest is distributed and in what land use/land cover context—factors that can substantially affect forest composition and health, wildlife, water quality, and forest management. In this paper we examine which fragmentation and context metrics should be linked with FIA plot data and monitored over time, and we identify possible sources of land use/land cover data from which to calculate this information. Emphasis is placed on those metrics that have been observed to be indicators of change in forested ecosystems. Using a complete set of photointerpreted land use/cover data in Massachusetts as the “truth,” we examine one possible source, the 1992 National Land Cover Dataset (NLCD) for its “fragmentation accuracy.” With accurate, relevant, and consistent fragmentation and context information, FIA will be able to better understand, interpret, and report on the state of the forest.

FIA data collected from extensive sample plots across the United States are reported in a variety of statistical and analytical publications. Such reports include valuable information on the amount of forest in a particular State, county, or watershed, as well as total tree volume, forest type, species composition, size and age classes, and so on. However, typically little data are collected and analyzed on

forest fragmentation—how that forest is distributed across the landscape. For example, we do not know whether those acres of forest occur as part of a large matrix or are distributed as many smaller patches. Nor do we know how isolated or connected those patches are, what land use/land cover context the forest is in, or how much of the forest is in interior vs. edge conditions. Figure 1 illustrates two areas of roughly equal

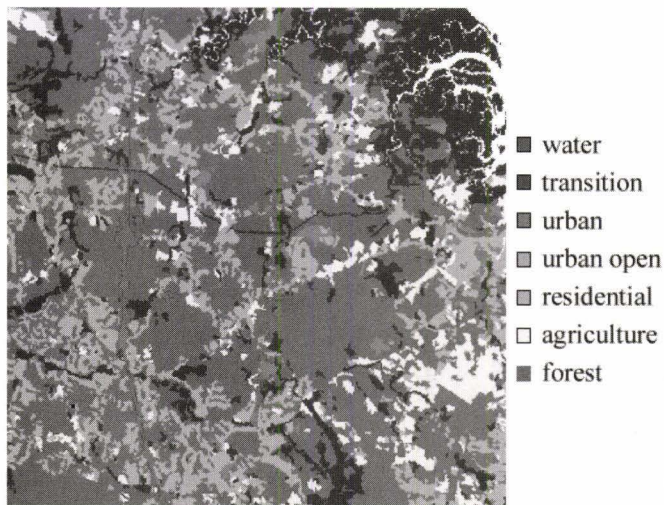


Figure 1.—Two areas of roughly equal forest area (61 and 62 percent, respectively), but different spatial distributions of forest and different contexts (primarily residential vs. primarily agricultural) that are not captured in the single percent forest statistic.

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amount forest² (61 and 62 percent, respectively), but different spatial distributions and contexts that are not captured by that single percent forest statistic.

Impacts of Fragmentation

The fragmentation of forest land has been observed to have a substantial effect on forest composition and health with respect to an increase in the number of exotics, mortality, and changes in composition (e.g., Airola and Buchholz 1984, Heckscher and others 2000, Saunders and others 1991, Zipperer and Pouyat 1995); water flow and flow variability, sedimentation, macroinvertebrates, and biogeochemical cycles (e.g., Hunsaker and others 1992, McMahon and Cuffney 2000, Richards and Host 1994, Wear and others 1998); wildlife abundance, diversity, and breeding success (Bolger and others 1997, Burke and Nol 2000, Cam and others 2000, Kurki and others 2000, Rosenberg and others 1999); and forest management in terms of economic viability and treatment constraints (e.g., Barlow and others 1998, Cooksey 2000, Wear and others 1999). Thus, there is an obvious need to analyze the FIA data with respect to fragmentation so that we can better understand, interpret, and report on the state of the forest. We also need to monitor distribution and fragmentation characteristics of the forest

² Percent forest equals the number of pixels classified as forest divided by the total number of pixels.

³ Collins, B. 1995. Aerial photo sampling instructions for the fourth inventories of Illinois and Indiana. Paper on file at the North Central Research Station, St. Paul, MN. 43 p.

⁴ Heilman, G.E., Jr.; Strittholt, J.R.; Slosser, N.C.; DellaSala, D.A. Forest fragmentation of the conterminous United States: assessing forest intactness through road density and spatial characteristics. In preparation. BioScience. Submitted July 30, 2001.

over time, just as we monitor the status and changes in forest area, volume, relative species composition, and so on (fig. 2).

Regional Efforts

On a regional basis, information on fragmentation and/or context has been collected in conjunction with FIA plot data in various ways over the years. In the Northeast, photointerpretation of sample point locations for six Eastern Coastal States was completed in association with inventories of these States in the late 1990s (Riemann and Tillman 1999). In Indiana and Illinois, patch size and land use data were collected via photointerpretation of an area around each FIA plot in a one-time effort in the mid-1990s to examine land use context (Collins 1995³). In Oregon, building densities were photointerpreted at sample point locations from aerial photographs taken in 1974, 1982, and 1994 to gather data on the effects of a range of human habitation on forest (Azuma and others 1999, Kline and others 2000). In the broadest effort, in the South and Southeast, data on fragment size and distance to road were obtained from aerial photography and ground inventory for all plots from 1974 to 1995, also providing a source of time-series information (e.g., Rudis 1995, 2001). Further analysis of this existing information resource in conjunction with FIA plot data will provide additional guidance with respect to the metrics of interest, relevant thresholds indicating probable or substantial impact, and experiences with different data sources and collection methods that focus on large areas. Data collected via photointerpretation are typically fairly accurate at those point locations, but these collection approaches are labor intensive and time consuming. At least two national efforts have generated complete coverage of numerous fragmentation metrics calculated from TM-derived sources (Heilman and others 2001⁴, Riitters and others 2000), but these measures are not necessarily at a scale that can be

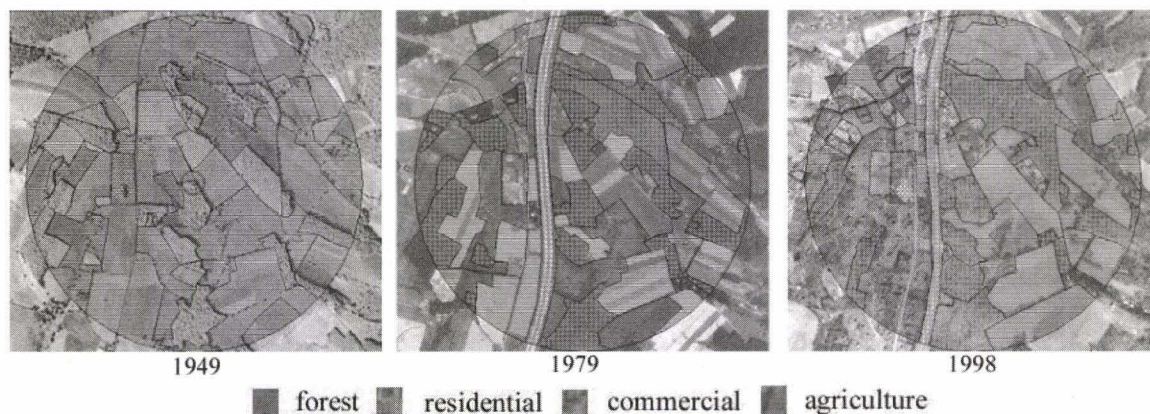


Figure 2.—Example of the changing context around an individual forested plot over time.

related to FIA plot data. Wendt (2001) related fragmentation metrics calculated from TM-derived land use-land cover maps to FIA plot data via the ~6,000-acre hexagon area in which each plot falls, but this approach limits the assessment of fragmentation and context to that one scale.

Definition and Measures of Fragmentation

Forest fragmentation is considered here to be the spatial breakup of forest by developed land uses. It is described by both the total amount of remaining forest and its distribution and configuration. Context, a related and important descriptive factor, is defined as the land use composition of the area surrounding a point, stream, or patch of forest. Together, these measures describe landscape characteristics of interest for their potential impact on forest systems. The specific metrics that are used to capture this information are important. Our first goal was to identify, from results and observations of other studies, an initial list of variables/metrics that are relevant to forest ecosystems and FIA plots. We then investigated how to measure/monitor these variables over broad areas and over time, taking into account both accuracy and cost. This paper describes the first portion of this study.

METHODS

Choosing Fragmentation Metrics

Numerous methods and metrics have been developed for measuring forest fragmentation and context (e.g., He and others 2000, McGarigal and Marks 1994, Mladenoff and DeZonia 1997, Wickham and Norton 1994, Riitters and others 1995). But which of these metrics should we calculate and retain as additional relevant variables in association with FIA plot data and summary statistics? First and foremost, we are interested in those variables that **are** related to real changes observed; i.e., that are truly indicators of fragmentation effects. Betts (2000) described this as "management relevance" in which "metric values can then be related to thresholds associated with ecological processes at the landscape scale." Ideally, these parameters can be affected by policy or management to address situations that are considered undesirable by the user. Next, since we are considering metrics for large regions or the entire country, we are also looking for basic measures that do not have special implementation problems, such as extreme sensitivity

to boundaries or area size, and that are consistent over broad areas. Third, because we are interested in monitoring fragmentation over time, we want metrics that are relatively robust to differences such as the resolution of data sources, because the availability of different data sources may vary over time. Finally, we want metrics that cover the full spectrum of characteristics of interest with little or no redundancy, and we want to avoid those compound/complex metrics that combine measures with conflicting or interacting relationships with forest ecosystems.

Given these criteria and the observations reported in the literature, we focused on metrics in three areas:

1. Percent cover of forest and other land uses.
(Landscape-scale factors continually show up as important and can even override local factors in their apparent impact on water quality, wildlife success, and so on.)
2. Distribution/configuration of the forest.
(For example, patch sizes and patch isolation continue to be linked to many of the changes observed with plant and animal species. Patch sizes also directly affect the economic viability of forest land for timber management.)
3. Edge.
(Edges between different land uses continue to show up as places where forest/nonforest interactions are occurring.)

Thus, in conjunction with standard area summaries of forest (e.g., county or watershed), one would, for example, calculate for each region the total core forest area (with and without roads); the percent area of each land use; frequency distributions of patch area, isolation, and shape; the total forest perimeter edge distance; and the percentage of the total forest edge bordered by each developed land use. It is important to retain and report the full frequency distribution with variables such as patch size because a single summary statistic cannot capture the range of information required and can even be in error or misleading. A frequency distribution is also important because of the range of issues potentially being addressed for which we may not yet know which threshold will be the most important indicator. When all of the data are retained and available in this form, any of those values can be extracted at any time (e.g., the largest patch size, the amount of forest in patches larger than 10 acres). In addition, because we are interested in summarizing such information for regions of interest, our database must include measures for each patch or

matrix such as total area, core area (with and without roads), patch isolation (e.g., nearest neighbor distance), a shape index, and list of the adjacent land uses and total perimeter distance of each. Finally, in addition to the region- and patch-level measures, the database must retain additional measures unique to each FIA plot, including distance from the plot to the nearest edge, the adjacent land use at that edge, and context calculated at various scales around the point of interest. Ideally, to effectively study the impact of fragmentation, we also need a measure of land cover history; e.g., the “encapsulation date” of that forested patch (Bastin and Thomas 1999), because the length of time an area has been isolated can have a substantial effect on what stage in the process we are observing. Acquisition of this historical information, however, was not addressed in this study.

The scale of calculation is an important consideration, and statistics calculated at several extents need to be retained in the suite of fragmentation statistics. Because we frequently do not yet know which extent is most strongly correlated with (has the most significant impact on) changes observed in forest health, water quality, or wildlife diversity, it is important to calculate statistics at multiple extents to determine the relevant threshold(s) of the impacts/changes observed. For example, in figures 3 and 4, if we calculated and recorded only the smallest surrounding area, we would be unaware of the substantial amount of residential area

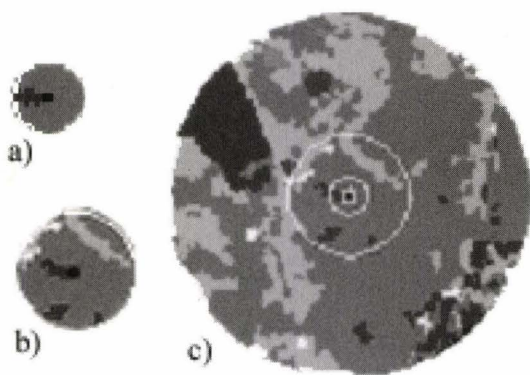


Figure 3.—Example of the effect of the window size or “scale of observation” on the summary statistics calculated. In a), a 50-acre area around a random forest plot, the report is a landscape context of 92 percent forest and 8 percent water (enlarged for illustration); in b), a 500-acre area around that same plot, the report is 80 percent forest, 13 percent residential, and 2 percent agricultural; in c), a 5,000-acre area around the same forest plot, the landscape context report is 28 percent residential and 59 percent forest.

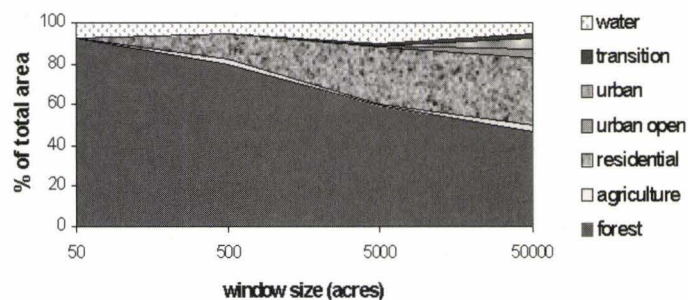


Figure 4.—Several scales of observation can be combined and displayed in a single plot such as this one. From this distribution, data from any window size of known interest (e.g., based on a particular species or known impact) within the range calculated can be extracted.

within only a kilometer or two of the plot. Similarly, if we recorded land use percentages for the larger window size only, we would lose the information that the surrounding 50 acres are entirely forested. If we isolate our information to just one window size, we will be ignorant of a substantial amount of context information.

Data Sources for Calculating Fragmentation Measures/Metrics

So, given the metrics we need, what source data are available? Two data sources have been used over broad areas: 1) visual interpretation of very high resolution imagery such as aerial photography or IKONOS imagery by point- or area-sample interpretation (e.g., Collins 1995³, Riemann and Tillman 1999, Rudis 2001), and 2) land use/land cover classifications derived from Landsat TM imagery (e.g., Heilman and others 2001⁴, Riitters and others 2000). The advantages of TM-derived fragmentation and context information are that it provides continuous spatial data and thus may provide better area statistics (visual interpretation of photography over large areas necessitates a sample approach), recalculating new indices from the same data is easier in digital format, coverage of large areas is much less expensive, and it is more likely that the desired image dates and repeat imagery can be obtained. The advantages of “photo”-derived fragmentation and context information are that it relates more directly to the scale of factors of interest on the ground, it relates well to individual plots if they are used as the sample points, and its accuracy generally is greater. Figure 5 illustrates some of the challenges with the accuracy of fragmentation statistics calculated from TM-derived imagery. In this example, all three data sets are

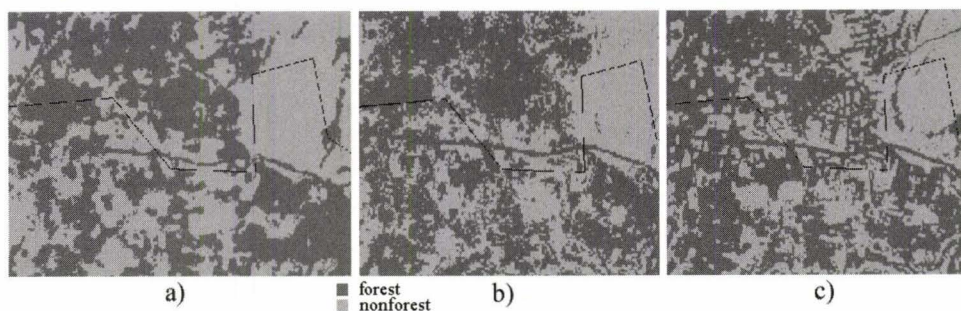


Figure 5.—Three data sets of approximately equal per pixel accuracy (~ 80%) but appearing to differ greatly in how they depict forest fragmentation. This results from the accuracy of the classification (e.g., are residential with trees classed as residential or forest, what are mixed pixels called, and so on), the resolution of the data, and the resolution of the classification. (Sources: a) is from the Gap Analysis Project (GAP), b) is from the NLCD'92 project, and c) is from an in-house classification. All are from approximately the same dates of imagery.)

approximately 80 percent accurate, yet they differ greatly in how the distribution and configuration of the forested areas is depicted. Even if the maps were 90 percent accurate in a per pixel assessment, the depiction of forest fragmentation can vary widely. Because TM-derived data sets are the most practical for broad areas, however, we chose in this study to try to push this data source to its limit first.

The accuracy of satellite-derived data sets, as in the percentages quoted above, is most frequently determined by a per pixel comparison of the classified data set with a “truth” data set of known ground or photo points. This can be modified and reported for individual classes or areas, or modified to allow for similar classes in a fuzzy accuracy measure. None of these, however, provide information on the accuracy of the spatial distribution of an individual class; i.e., the fragmentation accuracy of these data sets.

Because metrics *depend* on the accuracy of the source data, how can we first test the fragmentation accuracy of the data set so that we have an accuracy measure for the fragmentation and context statistics calculated from them? And given that the National Land Cover Dataset (NLCD) is the only nationally consistent data set currently available over broad areas, how accurate is it for the fragmentation and context metrics we are interested in? Can we qualify or even quantify this accuracy? And if there are metrics for which the accuracy is insufficient, what is the best way to acquire the necessary source information? Are there possibilities for post-processing the existing classification to improve its fragmentation accuracy? Or are there recommendations for improving the original classification that could be implemented in future national efforts? And what sampling

intensities would be necessary if visual interpretation of photography or high resolution imagery is required?

Study Area and Data Sets

Massachusetts was chosen as the initial study area because of the availability of a complete mapped photointerpretation of 37 land use/land cover classes from 1:25,000 photography, known as the MassGIS dataset.⁵ These data are continually updated in different parts of the State by new photointerpretation, and results from the latest photography (1999) should be available in the database soon. However, at the time the data were downloaded for this project, the available data came primarily from 1985 photography. The current NLCD was created using a largely unsupervised classification of 1992 Landsat TM imagery supported by aerial photography to label the classes and ancillary digital data sets such as USGS Digital Terrain Elevation Data (DTED), Bureau of the Census population and housing density data, 1970s USGS land use and land cover (LUDA) data, and National Wetlands Inventory (NWI) data to refine the classes. It was not spatially filtered to remove the salt-and-pepper effect of a per pixel classification (Loveland and others 1991, Vogelmann and others 1998). Due to differences in dates, and unfamiliarity with the details of the photointerpretation and image classification used, this comparison makes assumptions about the comparability of class definitions and the amount of land use change during this time period. These data were used here primarily to develop

⁵ Massachusetts Office of Geographic and Environmental Information. MassGIS landuse data. <http://www.state.ma.us/mgis/lus.htm>.

procedures and generate preliminary results that will be tested further with a more specifically developed photointerpretation data set and same-date imagery in the watersheds around the Delaware Water Gap.

Comparison with the MassGIS dataset highlighted already known errors with NLCD'92. For example, it depicts more forest than the MassGIS dataset in many areas even though it is from a later date (fig. 6). One reason for this is the tendency of NLCD'92 to misclassify residential-with-trees as forest. Also noteworthy is the difference resulting from the visual and context interpretation and minimum mapping unit of 1 acre in the MassGIS dataset as compared to the per pixel classification of NLCD'92. This has enormous implications for calculations of metrics such as patch size. For interpretations of land use (vs. land cover), both context interpretation (i.e., classifications influenced by context) and the use of a relatively small minimum area requirement were considered appropriate, so the MassGIS dataset was accepted as a closer model of the "truth."



a) NLCD (1992)



b) MassGIS (1985)

Figures 6a-b.—An illustration of some of the differences between the photointerpreted MassGIS dataset (1985) and the TM-derived NLCD'92 (zooming in to an area in northeastern Massachusetts).

Comparison Procedures and Preliminary Results

First, we checked both the "truth" and candidate data sets against the FIA data in terms of percent forest at the county level. This information can only be used as a flag if the data sets are wildly different, since the continuous data sets could potentially be more accurate than the FIA data for estimating amount of forest, particularly over small areas, given that they represent complete coverage rather than a sample.

Comparing percent forest estimates at the county level, the data sets produced estimates averaging within 10 percent of each other—NLCD'92 tended to overestimate county values by an average of 3.8 percent compared to values calculated from FIA plot data, and MassGIS tended to underestimate county values by an average of 5.5 percent compared with FIA data.⁶

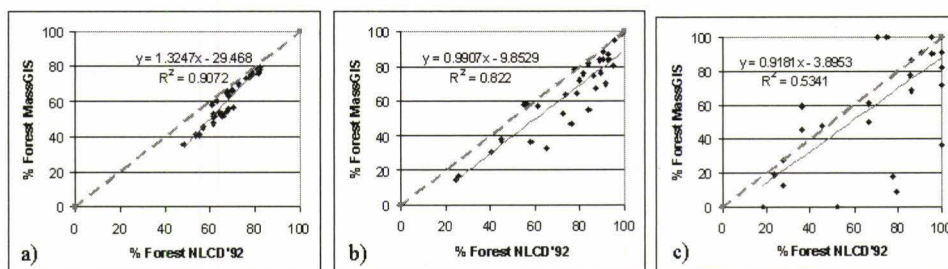
Next, we compared the two continuous data sets, the MassGIS and the NLCD'92, with respect to the most basic measure of interest—percent forest land—and determined the window size or "scale of observation" at which the relationship between our prospective data set and our "truth" began to break down. We randomly chose 30 points and generated six circles around each point with increasing areas of 5, 50, 500, 5,000, 50,000 and 500,000 acres (= circles of 0.08, 0.25, 0.8, 2.5, 8, and 25 km, respectively). The largest size approximated that of a county in Massachusetts. Within each area, we calculated the percentage of the land area occupied by forest and compared the estimate calculated from NLCD'92 with the "truth" calculated from the

photointerpreted data set (fig. 7). It became apparent that for areas of 500,000 acres, percent forest calculated from NLCD'92 agreed well with photointerpreted information (average absolute difference of 7.3 percent in an area 61 percent forested on average—well within what could be expected given the differences in data set dates). However, both increasing error (average absolute difference) and decreasing precision (standard deviation of the absolute difference values) were observed with decreasing extent. The average error was 11 percent at 500 acres, and 16 percent at 5 acres around those same 30 points (fig. 8).

These results provide initial guidance regarding the accuracy of estimates of the percent forest metric at each spatial extent.

We then compared other context measures such as percent of developed land uses within the area of interest, by percent of total area and percent of total forest edge. Accuracies of the percent by area measure, calculated as the average absolute difference between the two data sets at the 30 sample area

⁶ To remove as much time difference as possible, 1998 FIA plot data were used for comparison with the 1992 NLCD, and 1985 FIA plot data were used for comparison with the 1985 MassGIS dataset.



Figures 7a-c.—Comparison of estimates of percent forest calculated from NLCD'92 with those from the MassGIS dataset at three different window sizes: a) 500,000 acres, b) 500 acres, and c) 5 acres.

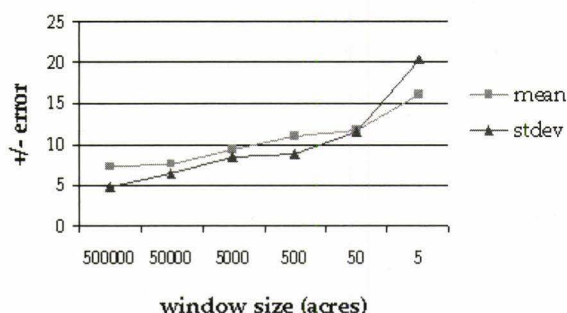


Figure 8.—Plotting the mean and standard deviation of the absolute differences between the two data sets indicates that there is both increasing error and decreasing precision with decreasing window size when NLCD'92 is used.

locations, were 4 percent for residential (in a region 14 percent residential on average) and 1.4 percent for agriculture (in a region 9 percent agricultural on average) for areas of 500,000 acres. This increased to 7 percent for residential and 4 percent for agriculture for areas of 500 acres (i.e., about half the size of the estimate itself) and to 13.6 percent for residential and 8.3 percent for agriculture for areas the size of 5 acres (i.e., approximately equal to the size of the estimate itself).

Finally, at the scales at which the basics of land use context appeared reasonable and/or at scales of particular interest, we examined other measures of interest, e.g., patch size. As expected, sizes of forest patch differed considerably between the two data sets. NLCD'92 missed a large percentage of the medium-size patches and was dominated instead by very small patches (1 to 5 pixels) and one enormous matrix patch. Thus, both the frequency distribution of patch sizes and the summary statistics calculated from the two data sets differed dramatically (see table 1). However, when we calculated patch-size statistics on just the core or interior forest of both data sets (in this case considering the outer 30 m to be edge), this substantially reduced the differences in statistics from the two data sets (table 1). Additional work is needed, but these results may indicate that patch-size statistics calculated from the total forest area are essentially meaningless, while those calculated from the “core forest” might be consistent enough to compare across both regions and time.

Aggregation index (AI) is a measure of connectedness/isolation that has been fairly robust to other problem areas such as changes in map resolution (He and others 2000). This metric was calculated for each Massachusetts county

Table 1.—Comparison of summary statistics calculated for patch size from both the NLCD'92 and the MassGIS data sets (total forest and core forest; all measurements are in acres)

Patch size statistic	All forest		Core forest	
	NLCD	MassGIS	NLCD	MassGIS
Maximum	42,585	2,679	3,240	1,736
Median	.180	.720	.270	.360
Mean	4.417	11.109	6.743	7.209

(forest class only). The AI estimates from the two data sets plotted fairly closely; i.e., for an index with values from 0-1, the average absolute difference in county-level AI estimates between the two data sets was 0.023, if the three counties that are less than 300 km² in area were excluded it was only 0.014. Also, the general pattern of the plotted values was similar except for the small counties. The poorer performance of AI at the smaller sizes suggests that minimum criteria for area may be necessary (fig. 9). Whether the magnitude of difference/error observed here is actually smaller than the

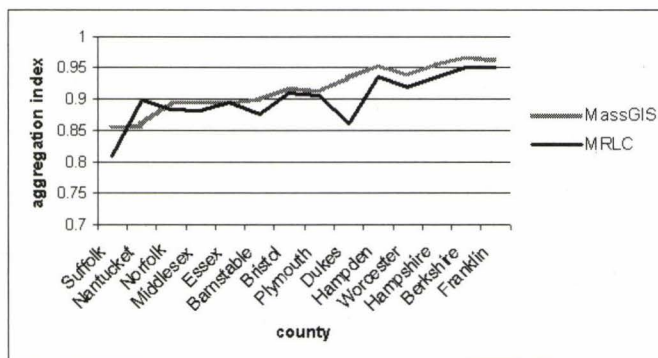


Figure 9.—Aggregation index of forest by county. Values calculated from NLCD'92 and MassGIS are compared. Counties are in order of increasing percent forest. The counties with the largest differences—Suffolk, Nantucket, and Dukes—are each less than 300 km² in size—about one-quarter the size of the next largest counties.

differences we would like to discern between regions or points in time for this variable needs to be investigated. Aggregation index is an example of a compound/complex metric that incorporates several different measures and thus may be less easily understood and therefore influenced by the land manager or regional policymaker. If the component factors of a compound/complex index are not conflicting in their effects, however, it can still be a useful monitoring tool, particularly if research reveals that the index is linked to changes in the forested ecosystem and thresholds can be identified at which those changes begin to occur. In addition, if it offers advantages such as robustness to differences not caused by real change (such as image resolution) and sensitivity to real changes in fragmentation status, such an index might even be desirable.

DISCUSSION/IMPLICATIONS/CONCLUSIONS

Many of the relationships between fragmentation and ecosystem change and the thresholds of fragmentation effects on forested systems have not been investigated, yet there is already evidence of the kinds of variables and metrics that do affect forested systems and even specific threshold guidelines for land managers (e.g., Rosenberg and others 1999). Concentrating on developing techniques to measure variables that have already been associated with or correlated with real changes in forest composition, water quality, wildlife, or forest management is a first priority. However, including a few additional metrics that have been proven to be both fairly sensitive to real differences in fragmentation status yet robust to image differences may also be worth monitoring in the early stages of metric/index development for FIA because of their implementation advantages. Iterative research regarding real impact and relevant thresholds using these data will tell us whether any index should continue to be monitored because of its observed links with real ecosystem change, or whether it should be dropped because of its observed irrelevance or inconsistency of measurement.

This initial study provides preliminary evidence that NLCD'92 has scale limitations even with respect to the most basic variables. However, if one can accept an error of +/- 11 percent (in an area averaging 64 percent forested) in the subsequent analyses using these data, one can calculate percent forest down to a context area of 500 acres (about a 800-m-radius circle). Measures such as patch size distributions (including mean patch size, average patch, and so on) are grossly inaccurate, although some post-processing such as considering only core forest in the calculations may bring the NLCD'92 data more closely in agreement with the photointerpreted "truth."

For future TM-derived data sets, an improvement in the classification of residential land uses will considerably improve the calculation of metrics for land use context. In addition, given the spatially varied/heterogeneous nature of some land use classes of interest (e.g., developed classes that contain a mixture of tree, building, grass, and road cover), classification algorithms that use context interpretations, and therefore that accurately classify, for example, mixtures of trees and houses as residential, will substantially improve both the accuracy and "fragmentation accuracy" of the data sets.

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TECHNIQUES AND CONSIDERATIONS FOR FIA FOREST FRAGMENTATION ANALYSIS

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ABSTRACT.—The Forest Inventory and Analysis unit of the Northeastern Research Station (NEFIA) is charged with inventorying and monitoring the Nation's forests. NEFIA has not gathered much information on forest fragmentation, but recent developments in computing and remote sensing technologies now make it possible to assess forest fragmentation on a regional basis. We describe several options for calculating landscape statistics and provide guidelines on their use.

The forests of the Eastern United States have been subjected to decades of conversion and regrowth due to human activity, insects and diseases, fire and wind damage, and other factors. This pattern of change has led to a mosaic of forest patches of varying sizes across the region. Forest patches vary in quality with respect to watershed protection, biomass sequestration, wildlife habitat, species richness maintenance, forest product production, aesthetic values, recreation opportunities, and other amenities. Forest fragmentation can thus greatly affect ecological systems and human activities.

Forest Inventory and Analysis (FIA) of the USDA Forest Service conducts periodic assessments of the quantity, quality, distribution and health of the Nation's forests (USDA Forest Service 1992). The Northeastern Research Station's FIA unit (NEFIA) periodically remeasures nearly 30,000 field survey plots across the Northeast. For each plot, data are collected on the size and distribution of trees, land use, productivity, ownership, and tree quality (USDA Forest Service 2000). From these data, statistical summaries are created and statistical reports are produced. Also published are resource bulletins (e.g., Widmann 1995), which provide more extensive interpretation of the data than do the statistical reports.

References to forest fragmentation are conspicuously absent from, or occur very infrequently in, most NEFIA statistical

and analytical reports because the FIA plot design is such that a given ground plot is meant to represent 6,000 acres. The plots are thus considered to be sparsely distributed if the goal is to characterize landscape features that occur at scales finer than this. Also, no data directly related to forest patch size are collected on the NEFIA plots, so any attempt to make inferences about forest fragmentation based on the plot data alone is questionable.

It is unfortunate that FIA does not report on the spatial distribution of contiguous areas or patches of forest in a detailed manner. Much depth of analysis is lost when only coarse-scale patterns are mentioned and generalizations about the distribution of forest across a State are given. As the Forest Service unit charged with reporting on the quantity, distribution, use and health of the Nation's forest resource, FIA should include in its reports detailed information on the spatial distribution and configuration of forest patches.

In this paper we present a methodology and offer guidelines for developing a protocol for FIA reporting on forest fragmentation using classified Landsat Thematic Mapper imagery from the USGS National Land Cover Dataset (NLCD) (Vogelmann and others 2001). This data set provides continuous coverage of land cover information across the United States and can be analyzed using well-defined spatial statistical methods that were, until very recently, impractical to implement at the State or regional scale. The choice of specific metrics, considerations of patch definition (a critical component of any fragmentation study), and the choice of specific data sources are described in Riemann and others (2001). Here we review currently existing, free, and commercially available software for conducting the spatial analysis, and we provide guidelines for implementing the assessment and interpreting the results.

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Review of Available Software

Fragstats

Developed as a shareware software utility for analyzing and quantifying landscape structure (McGarigal and Marks 1995), FRAGSTATS has since been incorporated into other shareware as well as commercial landscape analysis programs. The vector implementation of the program was written as a suite of Arc/Info Arc Macro Language (AML) programs (ESRI, Redlands, CA 92373). The raster implementation was written in the C programming language. There is currently a newer, GUI-based version of FRAGSTATS produced by programmers at the University of Massachusetts and available as shareware on the Web, but we do not have experience using it. Since raster data are the most widely available sources for raw fragmentation data on a regional scale, we will hereafter refer only to the raster capabilities of the software described here. A discussion of the full range of metrics that FRAGSTATS returns is beyond the scope of this paper; see McGarigal and Marks (1995) for specifics.

The most useful version of FRAGSTATS for landscape analysis at the coarse scale is the compiled DOS version of the raster implementation or the C version available for compilation on UNIX platforms. The program requires command line entry of parameters and prompts the user in a relatively straightforward manner for inputs. It accepts various image formats as well as ASCII text files in a special format. Program output is the fragmentation statistics in well-formatted tabular format and optional output images that assign each patch a unique patch-id. Indeed, this "patch grid" and its cross-reference to the original raster file form the basis for most of the programs and analyses described here. Although the raster implementation of the program is written in C, our experience is that for large landscapes; e.g., 20 by 20 km, FRAGSTATS is extremely slow or does not run at all. Because of this limitation and the difficulties associated with formatting input and output files, we did not choose FRAGSTATS as the software solution for regional assessments of fragmentation. The program can be useful, however, for assessments at a finer scale (e.g., townships).

Created by Elkie and others (1999), Patch Analyst is a shareware graphical interface for FRAGSTATS that runs as an extension to ArcView GIS (ESRI, Redlands, CA 92373)². The parameter entry is GUI-based and the user manual is written

clearly. One of the benefits of Patch Analyst is the ability to use ARC grid format raster files directly rather than the images that are required by the native FRAGSTATS implementation. The tabular output is formatted for quick import into a spreadsheet package, and any raster outputs are saved as Arc/Info grids. The major disadvantage, however, is that the user must operate within the confines of ArcView and its associated sluggish use of memory. As a result, processing time is much greater with Patch Analyst than with DOS FRAGSTATS, even though the basic programs are the same.

ARCVIEW AND ARC/INFO

The ARC software packages do not provide for analysis of landscape fragmentation analysis directly, but with a limited amount of knowledge of the command syntax, users can create many custom analyses that perform some of the same analyses as other bundled landscape fragmentation software. The commands that follow are very useful for fragmentation analysis. Each must be used with the ARC grid file format and in the GRID program within Arc/Info unless otherwise specified. When multiple areas within an image, such as counties, are to be analyzed, the command **gridclip** can be incorporated into an AML macro to create subsets of the original image. If gridclip does not perform well, a grid with binary values can be created from a vector representation of the study area using the ARC command **polygrid**, and this grid can be combined additively or multiplicatively with the image grid so as to create a subset that encompasses the study area. Contact the senior author for example code and for other ways to automate the following procedures.

1. **regiongroup**:

Regiongroup is the most fundamental of the grid commands for generating a landscape. It takes an integer ARC grid file (e.g., a classified satellite image converted to a grid using the **imagegrid** command) and assigns groups of contiguous pixels a unique patch-id (e.g., figure 1). There is a contiguity rule to define; i.e., the user must ask if he or she wants to include diagonal pixels or only pixels that are directly adjacent on the long side of the pixel to be evaluated. In figure 1, diagonal

pixels were considered to be members of a patch. Once the region coverage (hereafter, patch grid) has been created, one can simply examine its value attribute table (.vat) to derive information. The ARC commands **statistics** or **frequency** can be used to summarize the .vat when there are too many records for practical export to a statistical software package. The first part of table 1 is the .vat from the patch grid

(right) of figure 1. Note that 11 patches were formed from the input binary grid. Table 1 shows the patch-id, the count of pixels in that patch, and the value of the original grid that each patch represents (link). With this information, one can calculate an average patch area. Note that there are a large number of pixels for patch #2, which is actually the matrix, or nonforest background of the landscape, so including it in any

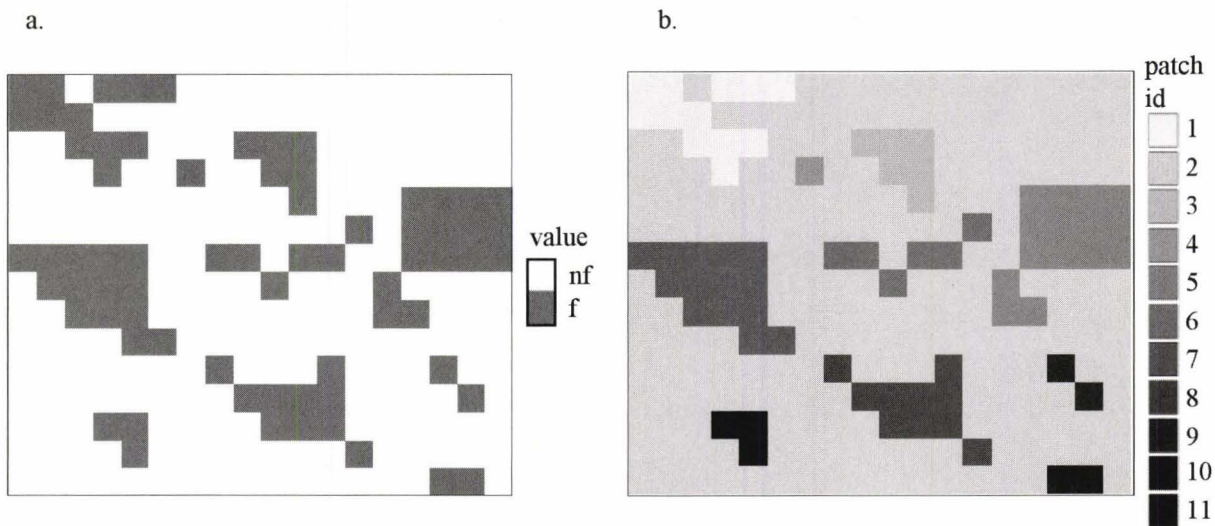


Figure 1.—a: Portion of an NLCD image that has been reclassified to forest (gray) and nonforest (white) using the Arc Grid command **reclass**. b.: Output of the **regiongroup** command (see text). Note that the contiguous areas of forest were assigned unique patch id values 1-11, and that contiguity was defined by the 8-neighbor rule (diagonal pixels are considered adjacent). Patch 2 is the matrix, or nonforest background. This patch should be excluded from analyses that might be skewed by its inclusion (e.g., average patch area).

Table 1.—Example of .vat of the output grid generated by **regiongroup** (Value, Count, and Link), merged to the output table from **zonalgeometry** (Area, Perimeter, Thickness, Xcentroid, Ycentroid, Major and Minor Axis, and Orientation)

Value	Count	Link	Area	Perimeter	Thickness	Xcentroid	Ycentroid	Major_Axis	Minor_Axis	Orientation
1	12	1	10800	780	15	2006588	2392070	73	46	173
2	199	0	179100	5640	51	2006776	2391882	259	219	16
3	6	1	5400	360	15	2006798	2392020	54	31	135
4	1	1	900	120	15	2006698	2392010	16	16	90
5	15	1	13500	660	45	2006970	2391934	87	49	43
6	6	1	5400	600	15	2006803	2391920	78	22	10
7	14	1	12600	600	45	2006599	2391885	89	44	147
8	10	1	9000	660	15	2006812	2391761	77	36	157
9	2	1	1800	240	15	2006983	2391785	41	13	135
10	3	1	2700	240	15	2006628	2391730	38	22	135
11	2	1	1800	180	15	2006983	2391680	33	16	0

calculation will bias patch metrics that are constructed by averaging individual patch values.

2. zonalgeometry:

Zonalgeometry is a command for assessing the geometry of each patch in the patch grid. Table 1 shows the area, perimeter, thickness (radius of the largest circle that can be completely contained by the patch), and various parameters that describe the ellipse that best approximates the patch's shape and location (centroid coordinates, major and minor axis length, and orientation). Average patch perimeter and area are common landscape metrics that help analysts better understand the composition of a landscape. Thickness and average axis length ratios can suggest the value of a landscape's patches for maintaining interior forest-dwelling species. Average distance between patch centroids can be calculated by converting the centroid coordinates to a point coverage using the ARC **generate** function, and then summarizing the output table from the ARC command **pointdistance**. Be advised that irregularly shaped patches and landscapes with a clumpy distribution of patches can confound this measure.

3. core areas:

Core areas are the internal portions of the patches that are not affected by edges, or interfaces between; e.g., forest and nonforest. They are probably the most useful landscape units with which to conduct an analysis because they are the most biologically meaningful. To create a core area grid, the user must first define an edge width of interest. A somewhat arbitrary choice might be 30 m for a classified Landsat Thematic Mapper data set; this would suggest that the analyst assumes that there is a 30-m buffer of questionable forest around the edge of a forested patch found on the original patch grid. Once this is decided, a user-defined filter can be created using ARC grid's **focal functions** or the **shrink** command, which shrinks the size of patches composed of specific classes; e.g., forest, by a specified number of pixels. The result is a grid for which the boundaries of the patches of interest are converted to either no data or the value of the matrix. As illustrated in figure 2, the patch-level statistics that are derived when examining only core areas derived with the shrink function will differ greatly from those derived when the entire landscape is used.

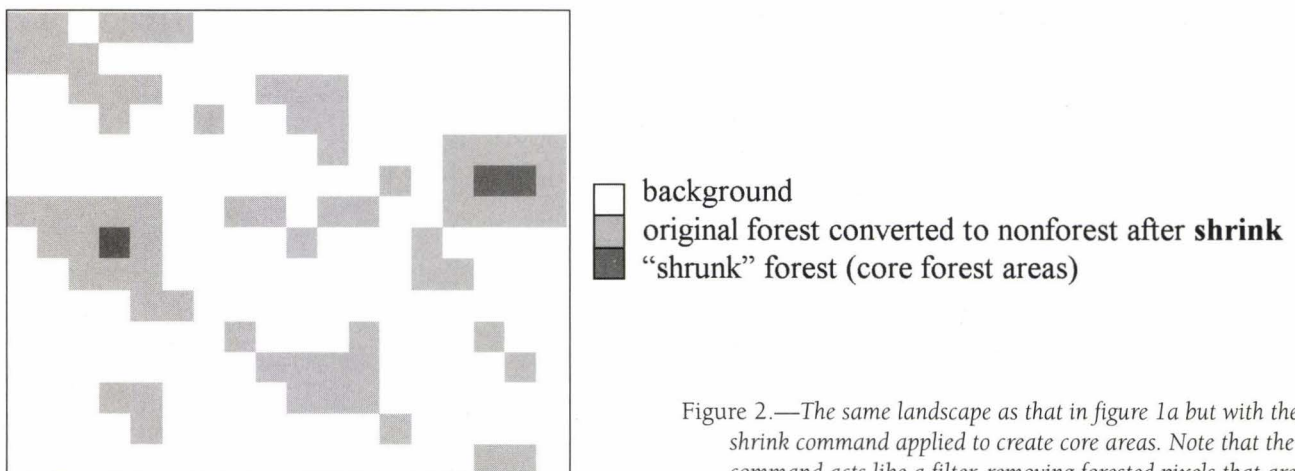


Figure 2.—The same landscape as that in figure 1a but with the **shrink** command applied to create core areas. Note that the command acts like a filter, removing forested pixels that are within 1 pixel of a nonforest boundary.

One also might wish to define meaningful areas of forest or create core areas by clipping out forest patches using roads. It is possible to convert U.S. Census Bureau Tiger Line Files (U.S. Census Bureau 2000) into grids by converting Arc coverages into grids using the **linegrid** command. Next, using one of the grid reclassification functions (e.g., **reclass**), each pixel is assigned a value of no data for road, 0 for no road. This new grid can serve as a mask for excluding analyses on tree-covered areas affected by roads (by using **setmask**) or as a way to split contiguous forest patches into smaller, more meaningful units (Heilman and others 2001)².

ArcView scripts and extensions that perform these analyses (e.g., Grid Transformation Tools and Grid Generalization Tools) can be downloaded free of charge from the ESRI Web site. They require Spatial Analyst, a commercial ArcView extension, however. Although it is appealing and convenient to work within the GUI framework of ArcView, it is not as stable as UNIX Arc/Info when processing large ARC grid file formats.

APACK

APACK was created at the University of Wisconsin's Forest Landscape Ecology lab as a shareware tool for processing large raster data sets consisting of landscape information (e.g., classified satellite imagery). It calculates many or most of the landscape statistics available from FRAGSTATS and some additional ones (see Mladenoff and DeZonia (2001) for details). Like FRAGSTATS, APACK has a command line parameter entry. Unlike FRAGSTATS, it does not interactively prompt the user for information, but this is only a slight inconvenience because the program's command reference manual is very easy to use.

² Heilman, G.E.; Stritholt, J.R.; Slosser, N.C.; DellaSala, D. [In prep.]. Forest fragmentation of the conterminous United States: assessing forest intactness through road density and spatial characteristics. In review; data and publication on file at the Conservation Biology Institute, Corvallis, OR 97333.

The authors of APACK report that its outputs compare closely with those of FRAGSTATS (we have verified this with our own tests), suggesting that the software is well written compared to FRAGSTATS. However, the primary advantage of APACK over FRAGSTATS is that the processing time is reduced dramatically. For example, with APACK, a 30-m NLCD image encompassing an area consisting of several tens of thousands of square kilometers can be processed in less than 15 minutes using a Pentium 500 MHz computer with 256 Meg of RAM. When the same analysis was run with FRAGSTATS, we experienced unexplained crashes and freezes. We later confirmed from discussions with colleagues that FRAGSTATS is not well suited for analyzing areas that are this large in a reasonable amount of time.

Another advantage of APACK is the flexibility and suitability of its output for direct transfer into a spreadsheet for processing. Formatting poorly organized output files is time consuming when hundreds of landscapes are analyzed in batch mode with FRAGSTATS or APACK. The following is a sample section of an APACK batch file that creates one run of APACK for each of several Massachusetts counties (coded 1, 3, and 5):

```
apack -f(gis) -UL(M) -UA(HA) -P(-) -
b(0) maforest1.gis maforest1.gisout aa
aan ai ap asm co col cor do dor ed pa
swd aa aan ai ap ar ed ede pa pac ps ra
sp
```

```
apack -f(gis) -UL(M) -UA(HA) -P(-) -
b(0) maforest3.gis maforest3.gisout aa
aan ai ap asm co col cor do dor ed pa
swd aa aan ai ap ar ed ede pa pac ps ra
sp
```

```
apack -f(gis) -UL(M) -UA(HA) -P(-) -
b(0) maforest5.gis maforest5.gisout aa
aan ai ap asm co col cor do dor ed pa
swd aa aan ai ap ar ed ede pa pac ps ra
sp
```

This batch file can be created easily in a spreadsheet by sequentially increasing the cell values containing the file names and copying the remainder. Note that in the previous example the general processing parameters precede the input and output file names, followed by a list of the desired metrics (see Mladenoff and DeZonia 2001 for a description

of the parameter entry). Note also that the input file extension is .gis, or ERDAS 7.x file format. This file format can be created directly in an image processing package like ERDAS Imagine (ERDAS, Atlanta, Georgia 30329) or by using the **gridimage** and/or **imagegrid** commands in Arc/Info.

Another advantage of APACK over other programs is that it provides adjacency matrices. The rows and columns of these matrices are the land use classes and the entries are the length of shared boundary between each combination of land uses. This information alone can dramatically increase a data consumer's understanding of the relationships between forested areas and their surroundings. For example, it is clear that two counties with equal areas of forest land can have a very different length of forest-agriculture and forest-urban boundary. A clear understanding of this difference will aid decisionmakers.

CONCLUSIONS

Analyzing the spatial distribution of forest cover is an essential component of reports by FIA and other Forest Service units that describe the distribution, quantity, use, and health of forest resources. With freely available software like APACK, one can rapidly produce fragmentation summaries for different-sized areas. NEFIA plans to produce county-level summaries of the APACK statistics and to make them available to both the FIA analysts and the public. As new data sources become available (e.g., the revision of the 1992 NLCD product (Yang and others 2001)), it will be possible to assess changes in fragmentation through time. Our aim is to increase the value of FIA statistical and analytical reports, to create new opportunities for analysis, and to broaden understanding of the forests in the Northeastern United States.

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POINT PATTERN ANALYSIS OF FIA DATA

Chris Woodall¹

ABSTRACT.—Point pattern analysis is a branch of spatial statistics that quantifies the spatial distribution of points in two-dimensional space. Point pattern analysis was conducted on stand stem-maps from FIA fixed-radius plots to explore point pattern analysis techniques and to determine the ability of pattern descriptions to describe stand attributes. Results indicate that the Ripley's $K(t)$ statistic may be readily calculated for FIA plots, providing an assessment of spatial pattern. Correlation was found between Ripley's $K(t)$ and stand disturbance history and forest type. However, spatial pattern assessment may be confounded by stands with few trees per acre. Basal area growth prediction using Ripley's $K(t)$ as a predictor variable is seriously limited by past stand disturbances. Although point pattern analysis may be limited by plot buffer creation techniques and the relatively small size of sample plots, extensive FIA sampling across the forests of the United States allows unprecedented spatial analysis of North America's forests.

Information concerning the spatial pattern of individual plants within plant communities may refine understanding of ecological processes (Hasse 1995, Legendre and Fortin 1989). Spatial patterns in plant communities are not only a record of past events, but they may also be a valuable predictor of future processes (Dale 1999). In forest stands, quantifying individual tree spatial patterns may provide information on forest establishment, growth, competition, reproduction, and mortality (Dale 1999). Point pattern analysis, a branch of spatial statistics, can be used to quantify the spatial pattern of plant communities (Cressie 1993). Point pattern analysis using FIA stem-mapping information permits refined analysis of past disturbance events, current forest type, and future stand growth on FIA plots. Such analyses permit the spatial investigation of forests at an unprecedented scale across the United States. A technique and possible benefits of conducting spatial point pattern analysis using FIA data are explored.

STAND-LEVEL POINT PATTERN ANALYSIS

Point pattern investigations may improve the assessment of forest attributes of FIA plots: forest growth, forest type, and

disturbance history. The spatial arrangement of individual trees in a stand may explain variations in stand growth patterns previously unexplained by current growth and yield models. Distance-independent diameter growth models do not explicitly account for the spatial aspects of tree data, but they indirectly accounted for spatial effects through inclusion of competition variables such as stand density (Lessard and others 2001). However, the assumption that competitive forces are applied equally throughout a stand is unrealistic for mixed-species, multi-aged forest stands or stands that are patchy due to disturbance (Moeur 1993). Clustering of trees has been found to decrease volume growth by up to 20 percent, compared to regular spatial distributions common to plantations (Miina 1994, Shao and Shugart 1997). Spatial statistics offer alternatives to the traditional broad population density investigations (Weiner 1982) by providing a methodology by which the spatial arrangement of individual plants may be quantified.

Spatial point pattern analysis has been used to investigate stand disturbance histories (Harrod and others 1999, Mast and Veblen 1999, Mateau and others 1998, Moeur 1997). It has commonly been found that as stands age, their tree point pattern shifts from that of a clustered distribution to that of a random distribution (Mast and Veblen 1999, Moeur 1997). Natural gap-disturbance events may increase clustering, while anthropomorphic disturbances, such as timber stand improvement operations, may increase uniformity.

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Spatial point pattern descriptions of stands have been used to describe the competitive interactions between trees in mixed-species forests (Duncan 1991, Szwagrzyk 1992, Ward and others 1996), which may in turn reveal successional pathways. It can be hypothesized that the spatial arrangement of shade-intolerant tree species will be less clustered than that of shade-tolerant tree species, due to species-specific self-thinning behaviors. As forests progress through stand development, from a species composition dominated by shade-intolerant species to those that may be more shade tolerant, one might expect a change in spatial point patterns. In addition to shade tolerance, younger species components of a forest community (more shade tolerant) may tend to be more clustered due to recent regeneration events. Whether as an indicator of stand history, growth, or forest type, spatial point pattern analysis may provide another stand variable of considerable value in ecological analyses.

RIPLEY'S $K(t)$

A widely used spatial statistic of point pattern analysis is Ripley's $K(t)$, a univariate second-order analysis of point patterns in a two-dimensional space (Dale 1999, Hasse 1995). The term "second order" refers to the analysis of all point-to-point distances, as opposed to first-order analyses such as "nearest neighbor" that use only the mean of inter-point distances (Dale 1999, Hasse 1995). With Ripley's analysis, a circle of radius t is centered at each spatial data point and the number of neighbors within the circle is counted (Hasse 1995). The variable t is often referred to as the step-size. For n individual points in the area A , the density ($D=n/A$) is the mean number of points per unit area (Hasse 1995). The $K(t)$ function gives the expected number of points within radius t of an arbitrary point under a prescribed distribution (Hasse 1995). If points are randomly distributed (following a Poisson distribution), then the expected value will not exceed a fixed threshold (Hasse 1995). Confidence intervals are calculated for this expected value using Monte Carlo simulations. Simulations entail randomly generating points for plots of the same size as the observed plot, with the lowest and highest values of $K(t)$ for each t used to estimate the lower and upper bounds of confidence envelopes (Hasse 1995). If the expected value for any size-step exceeds the value established by the confidence envelopes, then the null hypothesis of spatial randomness is rejected for that t (Hasse 1995, Mast and Veblen 1999). To achieve a 99 percent confidence interval, 99 simulations must be calculated (Mast and Veblen 1999).

Recent research suggests that toroidal edge corrections should be utilized (Boots and Getis 1988, Duncan 1990, Mast and Veblen 1999, Ripley 1977). Toroidal edge correction involves wrapping the plot around a torus such that opposite sides of the plot connect, creating a data set with no boundary (Hasse 1995, Ripley 1977).

OPERATIONAL CONSIDERATIONS OF PATTERN ANALYSIS

Two attributes of the current FIA sampling design confound point pattern analysis. First, the circular subplot shape does not allow for toroidal edge correction. Second, the FIA subplots may be too small to allow for robust spatial analysis. Point pattern analysis is usually conducted on rectangular plots substantially larger than current FIA sub plots. Hence, no literature exists to propose corrections for the confounding factors. Therefore, for this study, the subplots for each FIA plot were truncated to a square shape (excluding all tree locations outside a superimposed square) and all four truncated subplots were combined into one square for each FIA plot. The assumption is that the dispersive and attractive properties of point patterns will be maintained during subsampling and recombination, as long as a minimum scale of sampling is not violated. The toroidal edge correction method (Ripley 1977) replicates the point pattern of rectangular areas eight times and adjoins all eight rectangles for a seamless pattern. The adjoining of all four FIA-subplot point patterns is considered a process analogous to toroidal edge correction whose validity should be elucidated by this and future research.

OBJECTIVES

The study had two major objectives:

1. To examine the relationships between Ripley's $K(t)$ and FIA stand stem-map patterns, stand growth, stand disturbance history, and forest type
2. To determine the effect of plot trees per acre (TPA) on Ripley's $K(t)$ for individual FIA plots

METHODS

Ripley's $K(t)$ is computed using the x,y coordinates of every tree in a rectangular area. Because FIA data are collected using a

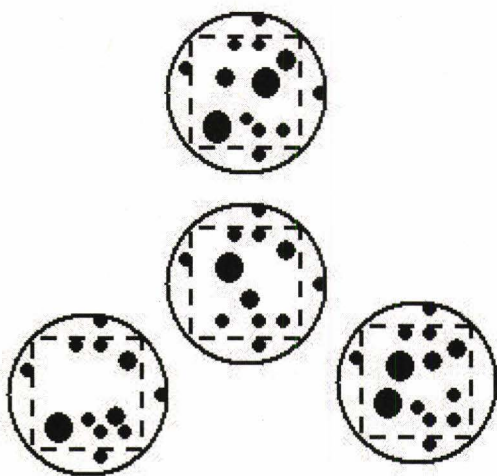


Figure 1a.—To allow buffer creation, all circular subplots truncated to a square.

four-subplot, fixed-radius sampling design, plot truncation and coordinate transformation are performed. First, the locations (azimuth and distance from subplot center) of trees within a superimposed square are extracted from every subplot (fig. 1a). Next, the distance and azimuth from plot center to each tree 5 inches and greater in d.b.h. are converted to x,y coordinates (using the lower left corner as the origin). Finally, the tree coordinates from each truncated subplot are combined to form a larger square with the lower left corner as the origin and 68-ft sides (fig. 1b). FIA data from Indiana were used (*Time 1*: 1998) (443 plots). To conduct growth analysis, remeasurement information for some of the plots measured in *Time 1* was used (*Time 2*: 1999 and 2000) (69 plots). Ripley's $K(t)$ and associated 99 percent confidence intervals were calculated for FIA plots in this study using spatial analysis programs written by Duncan (1990).

RESULTS/DISCUSSION

Point pattern analysis of FIA data has numerous limitations and caveats. First, the actual area of analysis is reduced due to buffer creation resulting in a substantial loss of data. Second, Ripley's $K(t)$ may only be calculated on data from the newly adopted four-plot fixed-radius sampling designs. All the previous surveys using variable-radius sampling designs cannot be used for spatial analysis. Third, Ripley's $K(t)$ may only be calculated for trees greater than 5 inches in diameter. The fixed radius for sampling of trees less than 5 inches in

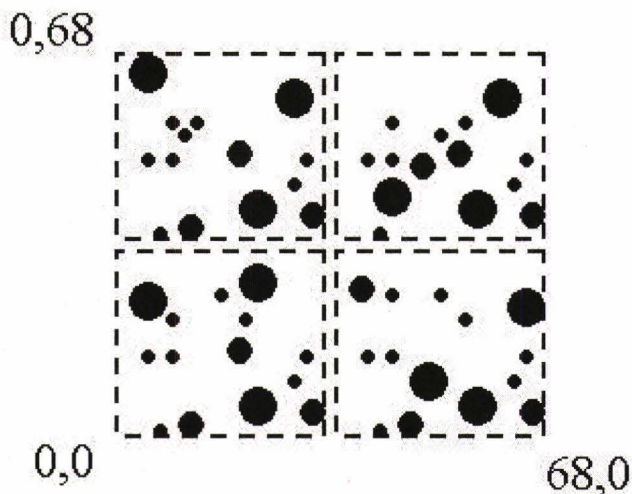


Figure 1b.—All square subplots combined to one plot square and all bearings and distances transformed to x,y coordinate system (ft).

d.b.h. is 6.8 ft, a size insufficient for broad deductions about tree spatial distributions. Fourth, because the FIA plots used in this analysis are actually a combination of subplots that are spatially disparate, plots located in ecotonal/multi-use areas may confound tree point pattern analysis; e.g., where one subplot is located on cropland while the other three are on forest land. The number of conditions and the actual ground land use classifications should be considered when calculating the Ripley's $K(t)$ statistic. Finally, to ease the data management requirements for spatial analysis of large inventories, a single step-distance (t) may need to be selected.

Although numerous limitations exist, for a large proportion of the forest land sampled by FIA, the Ripley's $K(t)$ statistic may prove to be an important measure of spatial character. From visual inspection of two FIA plot stem-maps, spatial arrangement differences are obvious (figs. 2 and 3). One distribution qualitatively appears random, while the other appears clustered. The Ripley's $K(t)$ statistic quantifies these apparent differences in tree spatial distributions. The stand that is described as clustered is significantly ($\alpha=.01$) clustered at scales between 12 and 28 ft according to the square-root transformed Ripley's $K(t)$ statistic (Busing 1996); i.e., its spatial distribution is significantly different from a random distribution (fig. 4). For the stem-map qualitatively described as random, the Ripley's $K(t)$ quantifies its spatial pattern as random across all scales of observation (null hypothesis of spatial randomness is not rejected) (fig. 5). Based on visual observations for over 400 stands, the Ripley's $K(t)$ statistic appears to correctly quantify the spatial patterns of FIA plots.

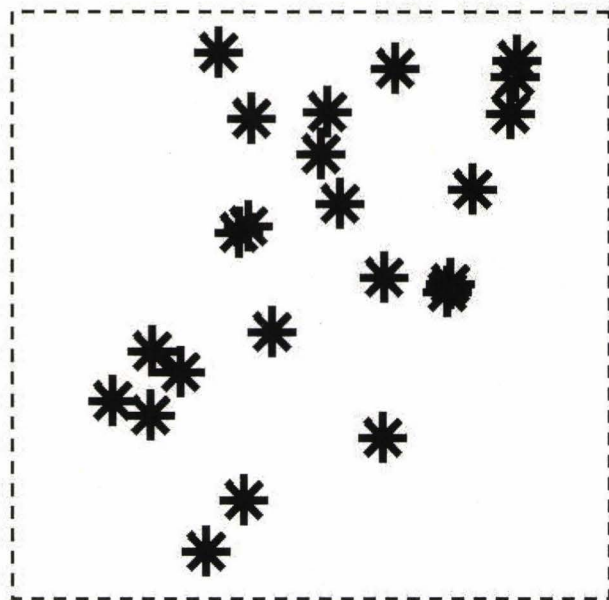


Figure 2.—Random distribution of individual tree locations

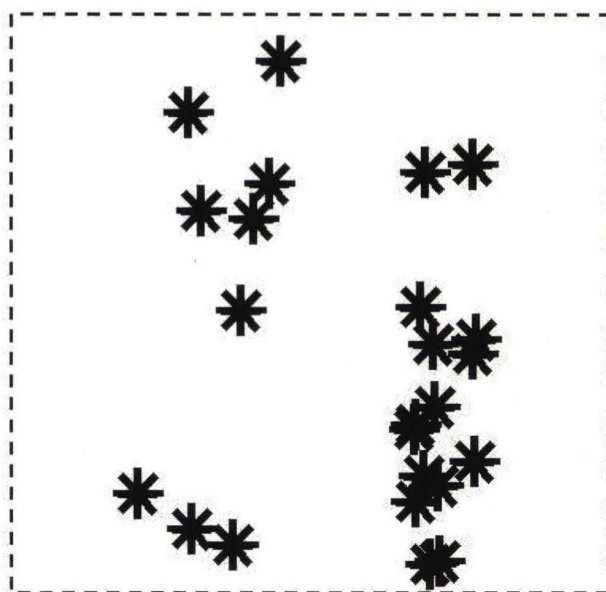


Figure 3.—Clustered distribution of individual tree locations
(Indiana, County 93, Cycle 4, plot 82).

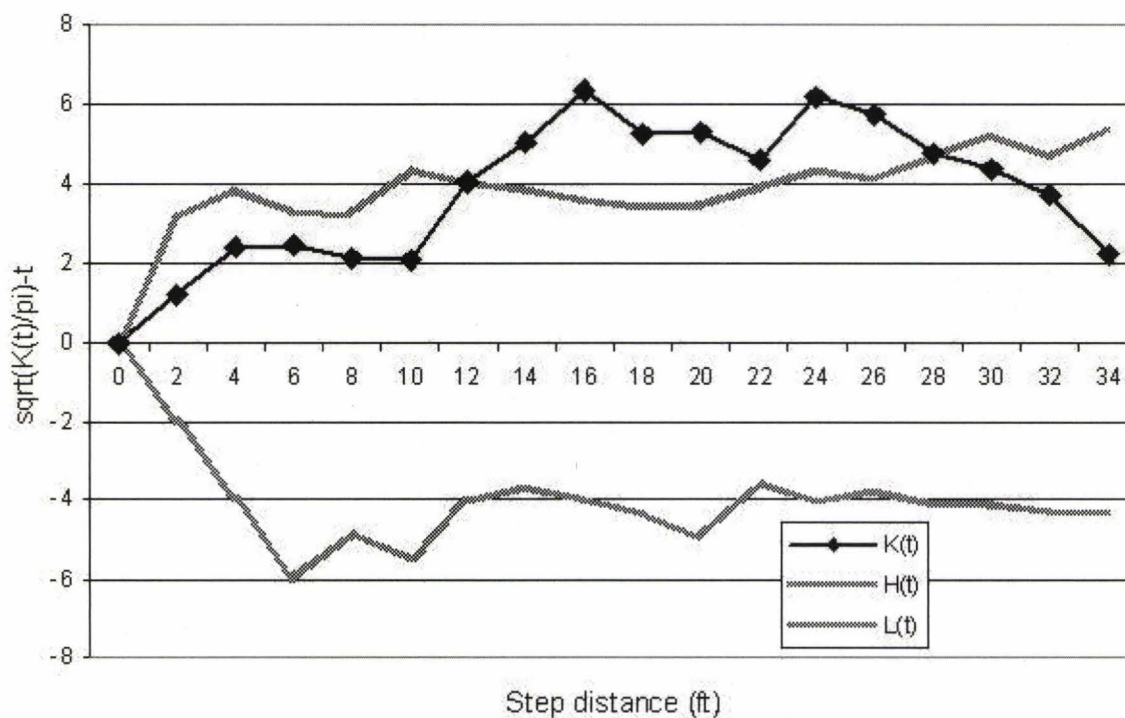


Figure 4.—Ripley's $K(t)$ and associated 99 percent confidence intervals for one FIA plot (Indiana, County 93, plot 82).

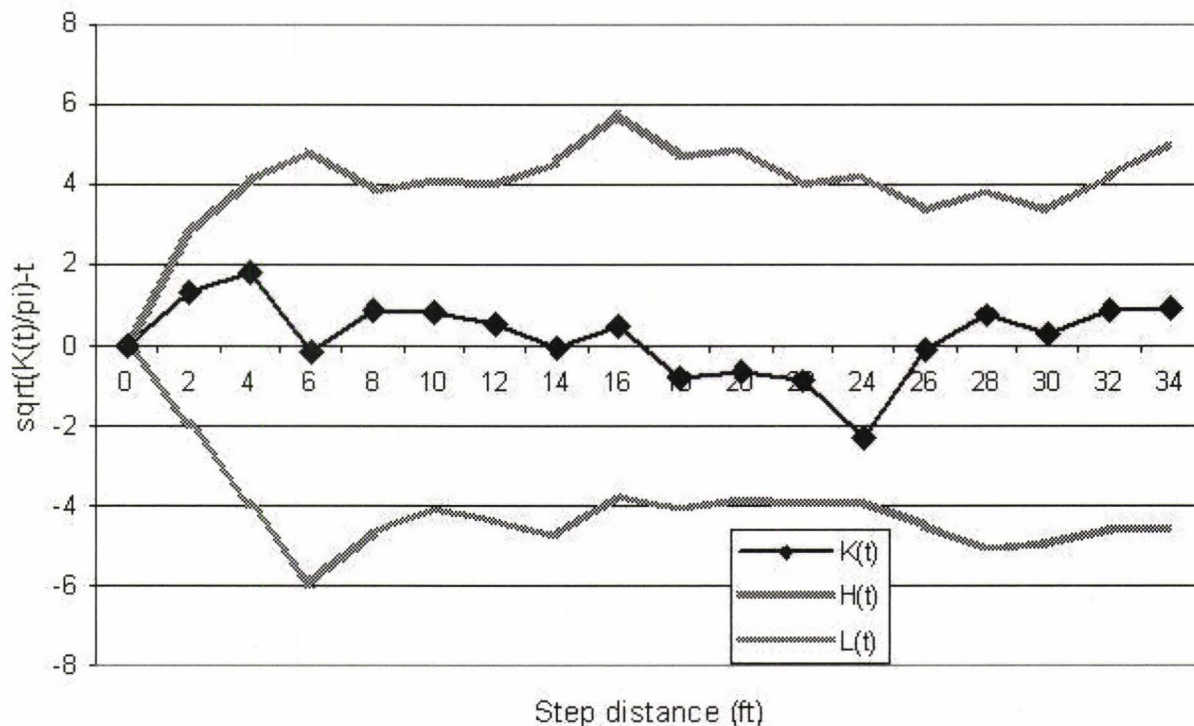


Figure 5.—Ripley's $K(t)$ and associated 99 percent confidence intervals for one FIA plot (Indiana, County 167, plot 45).

Because spatial analyses of large forest inventory data sets may encounter a wide range of forest conditions, the effect of TPA on Ripley's $K(t)$ values was examined. Because Ripley's $K(t)$ was computed for all step-size distance classes from 2 to 38 ft (2-ft step-sizes), one distance class (24 ft) was chosen as a basis of comparison. This step-size appeared to be a distance at which the $K(t)$ values stabilized and were usually indicative of clustering or randomness. Using the step-distance of 24 ft, the range of Ripley's $K(t)$ values increase with decreases in TPA (fig. 6). Ripley's $K(t)$ formulation strictly operates on coordinates, not on the size of individual trees. It would be expected that other measures of tree density such as basal area would have a less robust relationship with Ripley's $K(t)$ values. Stands with low TPA may have a greater ability to express clustering tendencies when using only one step-distance as a basis of comparison. Therefore, only FIA plots with at least a fixed minimum number of trees should be used in spatial analysis due to the possibility of extraneous Ripley's $K(t)$ values in plots with low TPA.

The relationship between Ripley's $K(t)$ values and percentage changes in stand BA for occupied stands ($BA > 100$ sq ft/ac)

was examined. Using a step-distance of 24 ft, the Ripley's $K(t)$ value increased for individual stands as the percentage growth in stand BA increased (fig. 7). This result is counterintuitive—as stands became more clustered, stand basal area growth increased. Stands that had spatial distributions that tended toward uniformity (lower $K(t)$ values) experienced losses in basal area (fig. 7). Stands with a propensity towards a uniform spatial distribution may have experienced disturbances (mortality or removals) during the remeasurement interval that reduced stand BA. When using spatial pattern information to refine stand growth predictions, past stand disturbances should have a confounding effect. Disturbances may increase individual tree growth, but reduce interim levels of stand growth.

The relationship between stand BA and Ripley's $K(t)$ may be more driven by recent disturbance history than density/yield theories. Mean Ripley's $K(t)$ values varied according to type of disturbance (fig. 8). Natural disturbances (windthrow, insects, disease, or fire) had the highest mean $K(t)$ values, while timber stand improvement (TSI) disturbances had the lowest mean $K(t)$ values (fig. 8). Partial stand cuttings and undisturbed

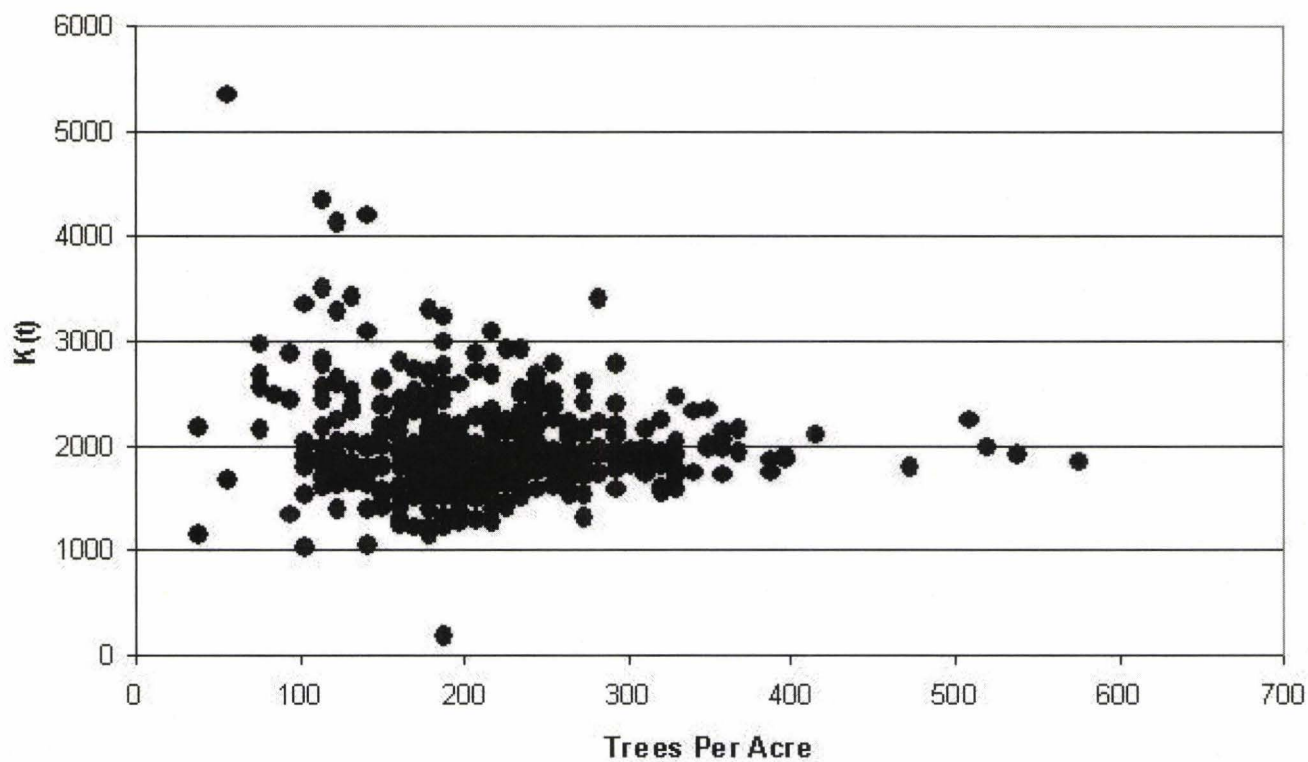


Figure 6.— $K(t)$ versus Trees Per Acre for FIA plots (Indiana, Cycle 4, $t=24$ ft).

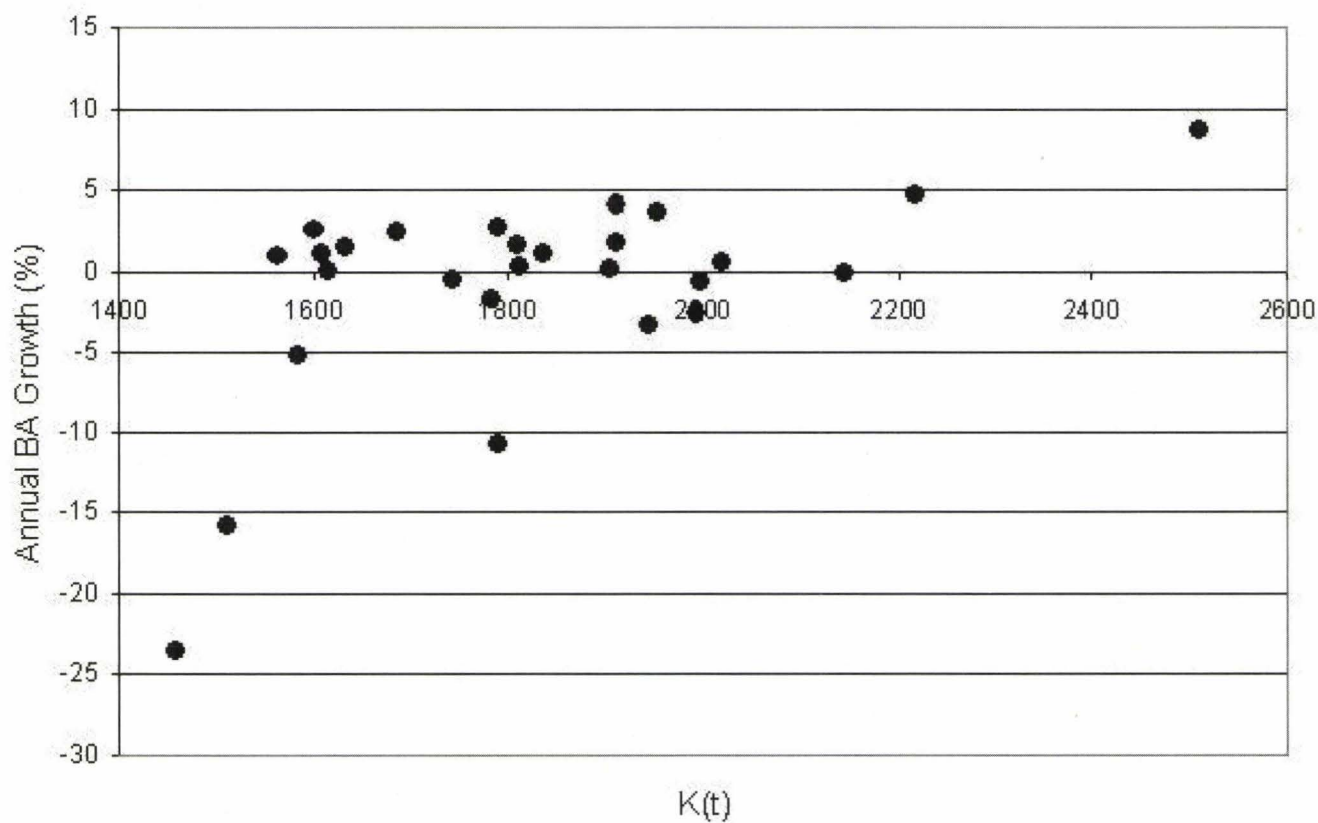


Figure 7.—Ripley's $K(t)$ versus annual BA stand growth (%), total BA > 100 sq ft, Indiana, $t=24$ ft.

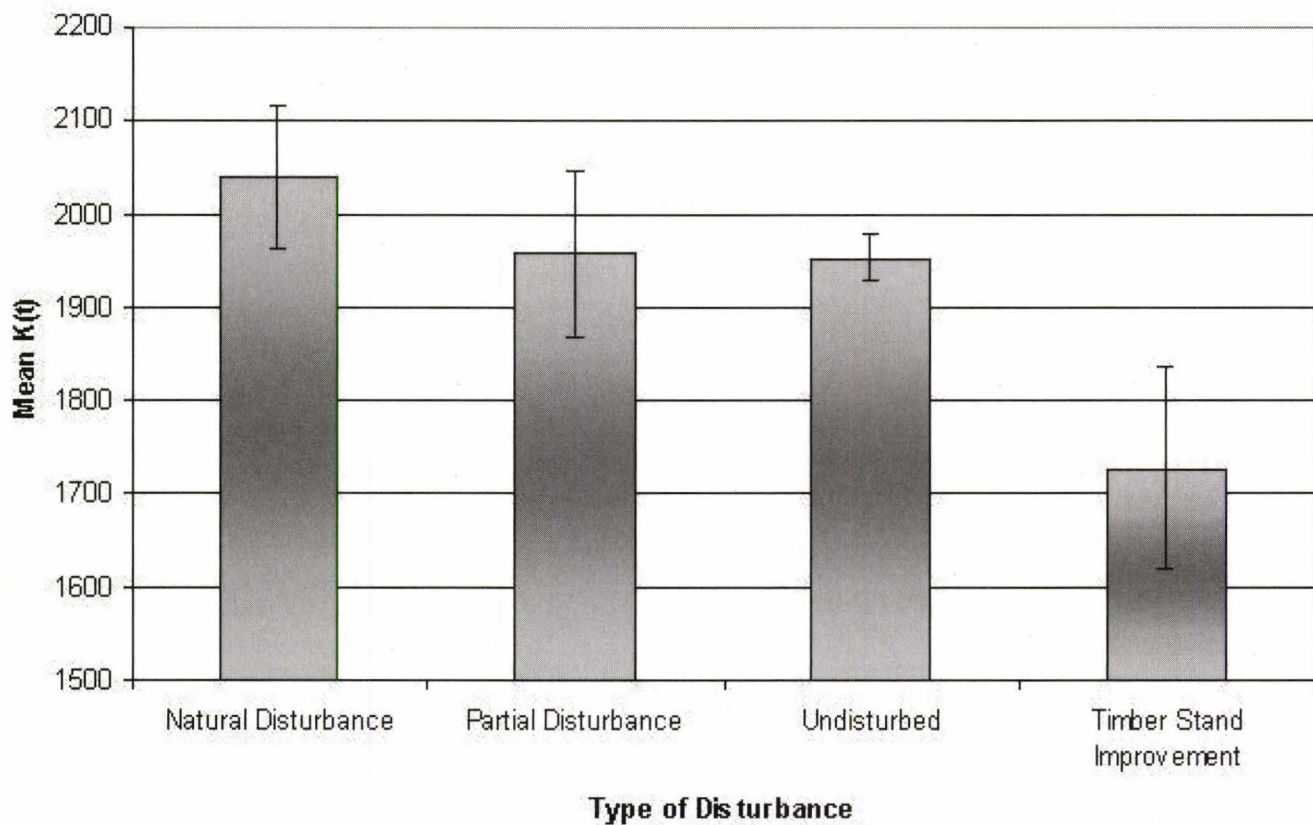


Figure 8.—Mean $K(t)$ values and associated standard errors for stands by types of identified disturbances ($t=24$ ft, $n > 20$).

stands had nearly the same mean $K(t)$ value (fig. 8). Trends in mean Ripley's $K(t)$ values across different stand disturbance types may be explained by the inherent spatial attributes of these disturbances. Natural disturbances, such as sub-acre-scale gap disturbances, may increase the clustering nature of tree patterns. Selection thinning, which may remove only certain size or age classes, may only moderately increase the dispersion nature of stands. TSI treatments may actually increase uniformity due to the treatment's objectives of reducing competition experienced by individual trees and removing cull trees.

Mean Ripley's $K(t)$ values varied across selected forest types in Indiana (fig. 9). Mean $K(t)$ values appeared to increase with the increasing shade tolerance of the constituent tree species of each forest type (fig. 9). The oak and pine forest types collectively had lower $K(t)$ values when compared to the more shade tolerant ash, elm, and maple forest types (fig. 9). Shade-intolerant species may resist clustering more than shade-tolerant species that are more adapted for the shading of spatial clustering. Further research should be directed at understanding the spatial dynamics of species through the temporal progression of succession. Eventually, point pattern

analyses of FIA data may aid forest typing efforts and predictions about future forest successional trends at large temporal and spatial scales.

CONCLUSIONS

Spatial statistics may refine the assessment and prediction of forest change. Ripley's $K(t)$ may be easily calculated for all FIA plots, while affording valuable ecological information. Most of the limitations concerning application of Ripley's $K(t)$ involve plot buffer creation and analysis of plots of a relatively small size. Preliminary results using data from the four-plot fixed-radii FIA sampling designs indicate that Ripley's $K(t)$ may quantify the spatial point pattern distribution of individual plots. However, plots with relatively low TPA may have extraneous Ripley's $K(t)$ values. The ability of Ripley's $K(t)$ to refine prediction of stand basal area changes is confounded by past disturbance events, which often determine the spatial pattern of stands in subsequent years. The Ripley's $K(t)$ statistic may differentiate between disturbed and undisturbed plots, while also possibly indicating what disturbance may have occurred. Ripley's $K(t)$ values may also indicate forest type due

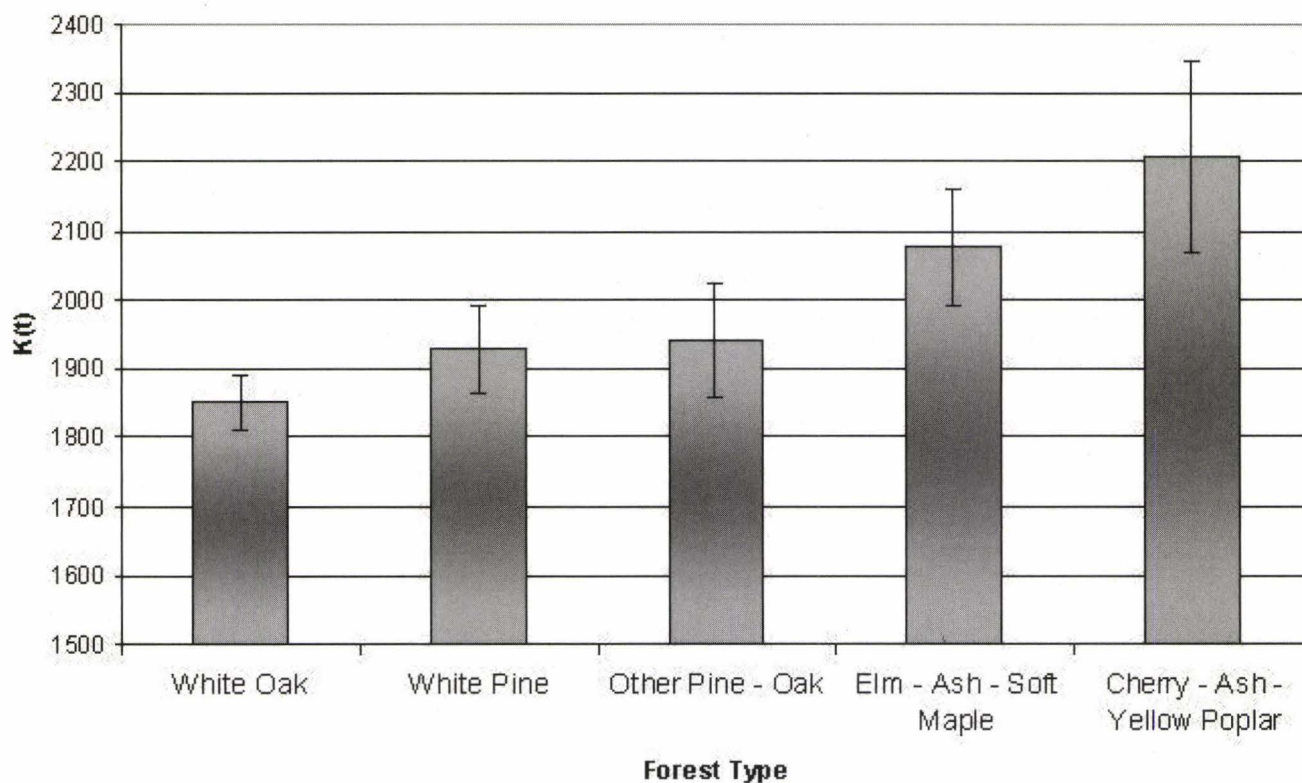


Figure 9.—Mean $K(t)$ values for various forest types—Indiana.

to the characteristic shade-tolerance ranges of constituent tree species. Given the small data set of this study and the diverse applications of spatial point pattern analyses using data from the FIA fixed-radius sampling design, numerous research possibilities exist and warrant consideration.

ACKNOWLEDGMENTS

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USING FIA DATA TO ASSESS CURRENT AND POTENTIAL FUTURE TREE SPECIES IMPORTANCE VALUES IN THE EASTERN UNITED STATES

Louis Iverson and Anantha Prasad¹

ABSTRACT.—FIA data are extremely valuable for evaluating regional variation in forest distribution. We have processed and summarized FIA data to show four patterns across the Eastern United States: 1) the number and density of FIA forested plots by state, 2) current importance values and frequencies for several species within 20 x 20 km blocks, 3) tree diversity by block, and 4) the potential future suitable habitat and migration of several species under two climate change scenarios.

FOREST INVENTORY ANALYSIS BY STATE

The latest FIA plot and tree data were downloaded from <http://srsfia/fia.srs.fs.fed.us>. Nearly 3 million tree records were aggregated to about 110,000 plots in 37 Eastern States. These plot-level data were summarized to give statewide statistics. Percent forest estimates were highest for Maine (89% forested), New Hampshire (87%), West Virginia (79%), and Vermont (77%). The highest numbers of plots assessed by FIA crews per state were in Minnesota (12,141 plots), Michigan (10,274), Georgia (9,134), and Wisconsin (6,872). The same states obviously had the highest number of trees measured, including more than 400,000 in Minnesota, 365,000 in Michigan, 259,000 in Georgia, and 157,000 in Wisconsin. For states with >20 percent forest, the forest area represented by each forest plot ranged from 557 ha in Minnesota to 2,959 ha in Louisiana. Other states with high forest plot densities included Michigan with 719 ha of forest represented per plot, Indiana with 848 ha, Wisconsin with 914 ha, and Illinois with 932 ha per plot.

CURRENT SPECIES IMPORTANCE

Species importance values (IV) and relative frequency of occurrence were derived for all species present within all FIA plots. Importance values were calculated based on the relative density and relative basal area for both the overstory

and the understory and scales from 0 to 200. Relative frequency was calculated as the number of plots with the species present vs. the total number of plots in each 20-km grid cell. Frequency and IV were aggregated to a 20 x 20 km grid and mapped. Maps show distribution, abundance, and relative frequency of each of several species in 20-km cells. IV data for 80 species in the Eastern United States (mapped by county rather than 20-km cell) can be found on our Web site: <http://www.fs.fed.us/ne/delaware/4153/4153.html> (global change tree atlas).

BIODIVERSITY OF TREES

For each 20-km grid cell, all species as well as several groups of species were counted. Tree diversity was greatest in the southern Appalachians and the southern tier national forests (e.g., the Shawnee, Hoosier, Wayne, and Monongahela), with up to 50 species represented in a 20 x 20 km cell. Conifer diversity was concentrated primarily in the north (up to 11 species) and secondarily in the southeast (up to 8 species). Other patterns emerged for the distribution of pines, oaks, maples, and hickories. The higher diversity locations for pines were in the Southeast States and the northern Lake States. Oaks were more diverse in the southern half of the region. The richest locations for maples were in New England, the Appalachians, and the northern Lake States, while the hickories were most diverse in the Ozarks of Missouri.

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MAPPING FUTURE POTENTIAL SPECIES IMPORTANCE

Potential future suitable habitats were evaluated for the Hadley and Canadian Climate Center (CCC) climate change scenarios via the empirical model, DISTRIB, which uses a regression tree analysis approach. Migration potential over the next 100 years was then evaluated via the stochastic model, SHIFT, which accounts for historical migration rates and fragmented habitats. Merging of the two models provides a reasonable tool to predict possible species migration into suitable, but fragmented habitats. For

southern U.S. species, potential suitable habitat expands much more with the CCC scenario than the Hadley scenario. The outputs of DISTRIB for 80 species can be found on our Web site listed on previous page (as can citations on this work). For species analyzed with SHIFT, high probabilities of migration occur primarily within 10 km of the current distribution boundary, with a low probability (<2% probability of colonization) of long-distance dispersal out to as far as 500 km from the current boundary. The model suggests that migration rates will be limited by fragmented landscapes and low abundance near the boundary. Migration rates may also be limited by unsuitable habitat northward (e.g., edaphic or climatic conditions).

WHAT DOES NONFOREST LAND CONTRIBUTE TO THE GLOBAL CARBON BALANCE?

Jennifer C. Jenkins¹ and Rachel Riemann²

ABSTRACT.—An inventory of land traditionally called “nonforest” and therefore not sampled by the Forest Inventory and Analysis (FIA) program was implemented by the FIA unit at the Northeastern Station in 1999 for five counties in Maryland. Biomass and biomass increment were estimated from the nonforest inventory data using techniques developed for application to large-scale inventory data. Results were compared to estimates for forested land in Maryland. We conclude from this work that carbon (C) stocks and fluxes on nonforest land could add substantially to current estimates of local, regional, and national C balances, which are currently based on forest land only.

Attempts to quantify the global carbon (C) budget have focused heavily on the role of forest growth and regrowth in C uptake (Caspersen and others 2000, Pacala and others 2001, Wofsy 2001). The forest inventory approach, because it is typically based on ground-measured data for a comprehensive, unbiased sample of forest land, has widely been accepted as the most reliable approach for large-scale and comprehensive estimation of forest C stocks and fluxes (Goodale and others 2002, Hicke and others 2002, Pacala and others 2001). The United States (U.S.) forest C budget (Birdsey and Heath 1995, U.S. Government 2000), however, is based exclusively on land defined by the U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis (FIA) program as “forest.”

FIA defines a stand of forest land as: a) at least 1 acre in size; b) at least 120 feet wide; c) at least 10 percent stocked; and d) not developed for another use (such as residential, recreational, or agricultural) (Hansen and others 1992). Based on this definition, roughly two-thirds (67%) of the U.S. land base is considered nonforest (Smith and others 2001). This nonforest figure includes range and desert land in the arid interior of the country; this arid land would not

normally support forest vegetation. Still, this definition of forest has critical gaps with respect to large-scale C cycle estimation, especially for regions such as the Northeastern U.S., where trees and other vegetation are ubiquitous on land being used for all types of purposes.

While inventories of trees in urban areas do exist (Nowak 1994, Nowak and Crane 2002), these urban samples have been almost exclusively conducted within the city limits. As a result, they do not include those areas missed from the FIA “forest” sample in suburban, rural-residential, and rural-agricultural areas outside the city limits. In this study, we examined the potential implications of excluding nonforest land from the land base used to develop large-scale C budgets.

METHODS

The Maryland Nonforest Inventory

In 1999, a pilot study was undertaken to inventory the plots classified by FIA as “nonforest” in five Maryland counties: Anne Arundel, Baltimore, Carroll, Harford, and Howard (fig. 1). This five-county area covers 2,237 mi² and is home to 2,512,431 persons, according to the 2000 U.S. Census. It was selected to capture a gradient of population density, urbanization, and land use. In addition, the region is identical to the five-county area designated as the research site for the Baltimore Ecosystem Study (BES), one of 24 Long-Term Ecological Research (LTER) study sites across the U.S.

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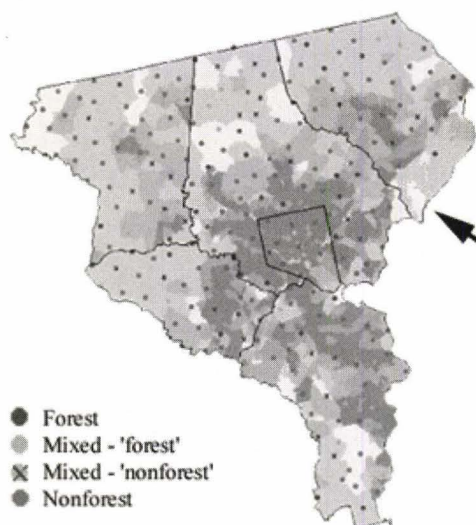


Figure 1.—The five-county study area and all 243 FIA plots. Any FIA plot with nonforest occurring at the center subplot was visited by the nonforest crew. This included both the “nonforest” and “mixed-nonforest” plots (i.e., some nonforest condition at the center subplot). From Riemann (2003).

Within the study area, the city of Baltimore is entirely urban, while large areas of suburban development occur in four of the five counties. Population density ranges from 336 to 8,059 persons per square mile in rural-agricultural Carroll County and Baltimore City, respectively. The pilot nonforest inventory was conducted concomitant with the Maryland inventory in 1999; this timing increased the efficiency of data collection, because the nonforest field crews collected the standard FIA plot variables for nonforest plots as well as the additional variables required by the nonforest inventory. By collecting data for the forest and nonforest inventory simultaneously, we also ensured that the two inventory samples would be comparable.

Details of the nonforest inventory procedure are given in Riemann (2003). Briefly, the nonforest inventory used the regular FIA plot grid in Maryland. A one-tenth-acre (37-ft-radius circular) nonforest plot was established around the center of subplot 1 if any nonforest condition occurred on that subplot (fig. 2). The nonforest portion of that one-tenth-acre plot was then inventoried by the nonforest field crew. A nonforest plot was not established if the center subplot was entirely forested, even if nonforest conditions did occur on any of the other subplots. The inventory methods and protocols used by the FIA nonforest inventory crew were identical to the standard FIA protocols wherever possible (USDA Forest Service 2000).

In 1999, there were 243 forest and nonforest FIA plots in the five-county study region. Of these, 146 were classified as nonforest, 44 as forest, and 53 as mixed (i.e., containing both forest and nonforest conditions). The mixed category contained 25 plots that were entirely forested on subplot 1 and 28 plots that had some nonforest on subplot 1. The nonforest crew inventoried 162 of these plots: 138 of the

nonforest plots and 24 of the mixed plots. Thus, eight of the nonforest plots and four of the mixed plots were not sampled by the nonforest crew; these plots are considered “missing,” and we assume that their exclusion does not bias this analysis.

On each plot, a subset of the standard FIA variables was collected, plus some variables designed to better describe the tree health, biodiversity, and ground cover of trees in nonforest areas. Those regular FIA variables that were considered to be less useful in nonforest areas, such as the timber-related variables of cull and board feet, were excluded from the nonforest sample. To better distinguish the types of areas in which the nonforest plots and areas of high tree basal area were found, three additional variables were added: detailed land use class, detailed owner class, and reason for nonforest status.

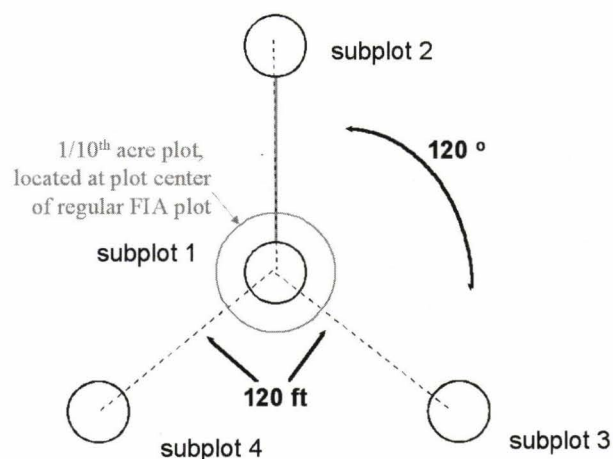


Figure 2.—Nonforest inventory plot design compared to standard FIA plot design. From Riemann (2003).

Biomass and NPP from Nonforest Inventory Data

Net primary production (NPP) is the rate at which C is accumulated by autotrophs and is expressed as the difference between gross photosynthesis and autotrophic respiration. Complete measurements of total NPP include annual aboveground and belowground production in both woody and non-woody biomass. In this study we focused on annual biomass increment only, also known as wood NPP (WNPP), for two reasons: a) we knew of no data on litterfall and root production for nonforest areas, and b) the wood component of NPP is the equivalent of annual C sequestration and storage, since wood biomass turns over much more slowly than the non-woody biomass compartments.

Total tree biomass and wood net primary production (WNPP) were computed from plot- and tree-level inventory data for the 162 nonforest plots in the five-county area in Maryland, using methods as described in Jenkins and others (2001a). WNPP was defined per tree as

$$\begin{aligned} \text{Wood production per tree (kg yr}^{-1}\text{)} = \\ \text{[aboveground biomass (kg) (}t_1\text{)] -} \\ \text{aboveground biomass (kg) (}t_0\text{)]/[}t_1 - t_0\text{ (yr)]} \quad (1) \end{aligned}$$

where t_1 refers to the current year, and t_0 refers to the year at the beginning of the inventory period (in this analysis we assumed a 1-year sampling interval, and found d.b.h. _{t_0} from d.b.h. _{t_1} as described below). Biomass estimates for current conditions (t_1) were found on a tree-by-tree basis from diameter at breast height (d.b.h.) using species-group regression equations as described by Jenkins and others (2003). To find biomass and biomass increment on a per unit area basis from tree-level measurements, the tree-level estimates were multiplied by the expansion factor representing the number of trees per unit area represented by that individual stem.

Because these nonforest plots have been censused only once, to obtain estimates of growth it was necessary to estimate d.b.h. growth for all trees. This was accomplished using linear algorithms developed for mid-Atlantic forests, which relate current diameter to predicted diameter increment (Jenkins and others 2001)

$$\begin{aligned} \text{d.b.h.}_{t_0} \text{ (cm)} = \text{d.b.h.}_{t_1} \text{ (cm)} - [\text{average d.b.h. growth rate} \\ \text{(cm yr}^{-1}\text{)}] * [\text{remeasurement period (yr)}]. \quad (2) \end{aligned}$$

Biomass values were converted to C using 0.475 as the proportion C in biomass (Raich and others 1991).

For comparison, biomass and WNPP were also computed for 316 remeasured forested plots in Maryland from the 1985 inventory using the same techniques. These values were further compared to biomass and WNPP data obtained using methods originally described by (Birdsey 1992), applied to timber volume growth and mortality data for Maryland and the entire Northeastern Region from the 1997 Resource Planning Act (RPA) assessment (tables at <http://www.fs.fed.us/fia/>).

To aggregate the nonforest inventory information from the five counties to the State level, an average nonforest biomass and WNPP value per unit area was computed for all 162 plots. No attempt was made to select plots with trees or on particular land types; as a result, this sample is assumed to be representative of the tree cover on an average piece of "nonforest" land in Maryland. This average per unit area biomass and WNPP value was multiplied by the nonforest land area in that State to approximate the aggregate State-level biomass and WNPP totals on nonforest land. A parallel procedure was followed for forest land in Maryland, except that the sample of forest plots was representative of forest land over the entire State rather than the smaller five-county region.

RESULTS

Maryland

Tree biomass stocks for Maryland forests computed using the Jenkins and Birdsey methods were comparable (table 1). The larger biomass stocks computed from the RPA data most likely occurred because the RPA data apply exclusively to timberland, which is selected for its high productivity. Tree biomass stocks for nonforest land in Maryland were, per unit area, roughly 25 percent of the biomass computed for forested land as computed for all forests (table 2). However, because there is a substantial amount of nonforest land in Maryland, the ratio of total biomass stocks on nonforest: forest land in Maryland was roughly 0.33 (table 2).

Per unit area wood production values for Maryland forests were also similar when computed using the Jenkins and

Table 1.—Biomass and WNPP statistics for Maryland and the Northeast

Forest	Maryland (Jenkins) (all forest)	Northeast (Birdsey) (RPA/timberland)	Maryland (Birdsey) (RPA/timberland)
Land area (thousand ac)	2,701	78,923	2,423
Average biomass (Mg C/ha)	72.25	67.01	81.07
Wood-biomass increment (Mg C/ha/yr)	1.90	1.91	2.87
Total C storage (x 10 ⁶ Mg C)	78.96	2,141.31	79.50
Annual C storage (x 10 ⁶ Mg C/yr)	2.08	61.06	2.82
Nonforest	Maryland (Jenkins)	Northeast	
Nonforest land area (thousand ac)	3,594	41,330	
Average biomass (Mg C/ha)	17.80	16.75	
Wood-biomass increment (Mg C/ha/yr)	0.42	0.42	
Total C storage (x 10 ⁶ Mg C)	25.92	280.23	
Annual C storage (x 10 ⁶ Mg C/yr)	0.61	14.45	

Table 2.—Ratios of nonforest: forest statistics for Maryland and the Northeast

	Maryland	Northeast
Forest land (thousand ac)	2,701	85,484
Nonforest land (thousand ac)	3,594	41,333
Nonforest: forest land area	1.33	0.48
Per unit area ratios		
Nonforest: forest biomass	0.25	assume 25%
Nonforest: forest WNPP	0.22	assume 22%
Aggregate State & region-level		
Nonforest: forest biomass	0.33	0.13
Nonforest: forest WNPP	0.29	0.24

Birdsey methods (table 1). The RPA data predicted somewhat larger wood-biomass increments; this is probably (again) due to the exclusion of nonproductive forests from the RPA sample. Per unit area, wood production on nonforest land was approximately 22 percent of wood production on forested land (table 2). As with forest C stocks, however, because of the large proportion of nonforest land in Maryland, the ratio of total annual C storage on nonforest: forest land was higher than this (table 2).

Northeast

To aggregate these values to the regional level for large-scale comparisons, we assumed that the Maryland ratios of nonforest: forest C stocks and fluxes are true for the region. Per unit area WNPP on all nonforest land in the region was therefore assumed to be 22 percent of wood production on forested land, and per unit area biomass on nonforest land was assumed to total 25 percent of biomass on forest land. In the Northeast Region (as defined by RPA), we calculate that nonforest land contributes about 280 million metric tons of C in tree biomass (one metric ton = 1 Mg = 10^6 g), or about 14 million metric tons every year (table 1). This adds to roughly 13 percent of the biomass and 24 percent of the WNPP on forested land (table 2).

DISCUSSION

There is widespread consensus that a "missing" carbon sink (i.e., the difference between C emitted from anthropogenic and non-anthropogenic activities on the surface of Earth, and the C sequestered in terrestrial and oceanic ecosystems or stored in wood products) of up to 1-2 Pg C yr⁻¹ (1 Pg = 10^{15} g) exists in terrestrial systems in the northern midlatitudes. Ongoing efforts to find the missing C using different measurement methods have yielded conflicting results (Birdsey and Heath 1995, Fan and others 1998, Schimel and others 2000), although current estimates are converging toward a U.S. sink between 0.35 and 0.90 Pg C yr⁻¹ (Pacala and others 2001). Forest inventory measurements currently suggest that forest trees in the United States remove between 0.11 and 0.15 Pg C yr⁻¹ from the atmosphere, but these estimates are currently based only on land classified by FIA as forest. If we assume that the ratios of forest: nonforest WNPP and forest: nonforest land are similar for the rest of

the United States, then nonforest land could add an additional 24 percent to this value. In other words, based on the results of this analysis, it is possible that trees on nonforest land are storing an additional 0.03 to 0.04 Pg C yr⁻¹. This could amount to 10 percent of the existing "missing" sink of 0.35 to 0.90 Pg C yr⁻¹.

While these results suggest that trees on nonforest land almost certainly contribute to overall C sequestration, much more research is needed to understand the dynamics of C stocks and fluxes in nonforest areas. For example, in this analysis, we have excluded all consideration of ornamental shrubs and grasses, which must sequester additional C. Soils in gardens and other cultivated non-agricultural areas are likely to harbor C as well, in near-direct proportion to the types of management these lands experience.

The diameter growth algorithms and the biomass regression equations used in this analysis were developed for forest trees. Research on urban trees suggests that open-grown urban trees have larger crowns but lower biomass values than forest trees (Nowak 1996). Their diameter growth rates are likely to be higher than those of forest trees, however. The chances are good that the WNPP values presented here for nonforest land in Maryland are too low, but the biomass values may be too high.

It is difficult to extrapolate the results of this analysis to the entire United States because the patterns of urbanization and land use change are likely to differ from region to region. For example, there may be very little nonforest land in rural states such as Maine. In arid regions, there may be little difference between biomass and WNPP in residential and non-residential areas. But these relationships may also be much more complex: it is possible that irrigation in arid regions may increase residential woody biomass and production. An analysis such as this one, conducted for urban areas in different regions across the country, should help to resolve the issue of nonforest, non-agricultural C sequestration.

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VARIOUS ASPECTS OF SUSTAINABILITY ANALYSIS IN GEORGIA

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ABSTRACT.—In 2001 the Georgia Traditional Industries Program (TIP³) sponsored a cooperative study at the D.B. Warnell School of Forest Resources, University of Georgia, to analyze the long-term sustainability of the fiber supply in Georgia. The subject of this study is relevant to a diverse array of disciplines, and it offers the opportunity to explore various aspects of sustainability not directly related to the supply of fiber or timber alone. Examples of such aspects include studies of biomass densities and production, carbon densities, sequestration and credits, and landscape changes. We describe some of the technical aspects of data pooling and compilation, program settings and assumptions, and initial findings relating to this study.

BACKGROUND

Georgia, located in the southeastern part of the United States, is the third fastest growing State in the country, but over 72 percent of its land is still in forest cover. Over two-thirds of Georgia's forests are owned by approximately 630,000 private landowners. Forest production is Georgia's highest valued agricultural commodity and one in which it leads the Nation. Georgia has nearly 24 million acres in commercial forest (approximately 65 percent of the total 36.8 million acres), which is more than any other State. Georgia's forest industry generates 177,000 jobs: 75,000 jobs in the forest industry directly and the remaining jobs in industries supporting forest products manufacturing. The annual economic impact of the forest sector in Georgia exceeds a \$21 billion contribution to the State economy

through both domestic and foreign markets, while the value of the harvested forest products alone in 1996 was \$1.22 billion.

Since 1993, Georgia has led the United States in the number of trees planted. In 1996-1997, over a quarter billion trees were planted in Georgia on almost a half million acres. In 1991, 2.6 million Georgians over 16 years old participated in some form of wildlife-related recreational activity, including fishing, hunting, and other non-consumptive wildlife activities. The economic impact of this recreation in Georgia was \$1.1 billion. The growth of trees in Georgia is very rapid compared to other parts of the country. In addition, much progress has been made in the area of forest management intensification with use of herbicides and fertilizers. Modern pine plantations in Georgia that are intensively managed can grow up to four times faster than comparable extensively managed or unmanaged plantations.

The State's forest industry depends on accurate fiber supply assessments and the ability to predict changes in available inventory. With the rapid changes in the status and conditions of forests in the South, there is a need for more frequent inventory surveys. It is important also to monitor changes in land use, urbanization, fuel loading, balance of growth to harvest, and various catastrophic events. Recent efforts in obtaining more accurate and timely inventory estimates through reorganization of the Forest Inventory Analysis (FIA) inventory methods and through the

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implementation of the Southern Annual Forest Inventory System (SAFIS) reflect the importance of inventory updates for the forest industry and economies of the Southern States.

Forest inventory in Georgia is undergoing extensive changes in design, field practices, and applied technology. Rapidly changing technology and the availability of remotely sensed data offer new opportunities to enhance the inventory and its applications. Yet, even the most accurate and timely inventory cannot give a clear description of the future states of forest resources because such states depend on future actions and management practices, which in turn are subject to existing laws and regulations. To examine various states of our future forests, we need to consider multiple assumptions and alternative scenarios of forest management practices and potential laws and regulations. We can do this through long-term simulations of the changes that might affect our natural resources. In the described study, we investigated the potential impact of various assumptions and forest management scenarios on the future of the forest resources in Georgia using long-term simulations based on the current FIA inventory data and other available GIS and Landsat TM imagery.

DATA

Our analysis uses inventory data combined with GIS information and satellite imagery, hypothesized management and silvicultural practices, and various economic rules to define and evaluate the impact of various scenarios. The bulk of the Georgia data we have used so far came from the plot-level FIA database. We used the FIA variables describing polygon area, SI (site index), and stand age directly (Hansen and others 1992). A definition of species group used in simulations requires additional database processing separately for each simulation.

Until 2001, the primary FIA data site was handled by the Southern Research Station in Asheville, NC, and provided by its Web server as the Eastwide Database (EWDB) (Hansen and others 1992), and Westwide Database (WWDB) (Woudenberg and Farrenkopf 1995). In 2000, the Forest Service began switching to the new system making all FIA data from periodic inventories available as the FIADB database from the Web site of the North Central Research Station in St. Paul, MN (Miles and others 2000). In addition, we obtained Master Record (MR) data directly from the Forest Service (Southern Research Station, Asheville, NC).

EWDB and WWDB databases (Hansen and others 1992, Woudenberg and Farrenkopf 1995) provide data from the last two periodic inventories for most of the States. Files in FIADB databases from the latest two periodic inventories were merged by conversion of EWDB and WWDB files to the same format. The structure was then extended to include space for the added variables in the new round of data collection. This new structure includes changes in the table design (seven tables instead of three), software for processing the data (Oracle™ database server), and a higher level of detail (all collected field variables are included in the database). The FIADB databases are also connected to the system for tables and maps creation called the Forest Inventory Mapmaker: <http://www.ncrs.fs.fed.us/4801/FIADB/index.htm>. MR data provide tree height measurements, but they are defined differently in different inventory cycles.

Our analysis requires information about the stands' expected growth and yield. This information can be approximated from available yield tables. Unfortunately, the available yield tables are often old, are not specific for various stand origins or cover types, and do not allow for simulation of intensive silvicultural treatments. One of the major problems is a lack of yield tables for deciduous species. Notwithstanding these limitations, every effort was made to obtain the most appropriate yield tables for each stand (e.g., Forbes 1961, Harrison and Borders 1996, Martin and Brister 1999, Nelson and others 1961, Pienaar and others 1996, Schumacher and Coile 1960).

ALGORITHMS FOR POPULATING THE PLOT DATA INTO STAND POLYGONS

Populating of the FIA data into forested areas was another challenge. Initially, we attempted to limit all the forested areas by polygons such that the boundary line between any two contiguous plots is midway between each respective FIA point, as illustrated on the example in figure 1. However, this appeared to be quite inconsistent with the areas that according to FIA analysis were supposed to be represented by each plot. In essence, each plot represents a certain acreage, which is expressed by each plot's area expansion factor. In the results of our first attempt, this was not the case since there is no connection between the polygon area and the area expansion factor of the plot. Therefore, we needed to develop an algorithm that included this plot expansion factor. To improve the data populating scheme, we incorporated additional information using county

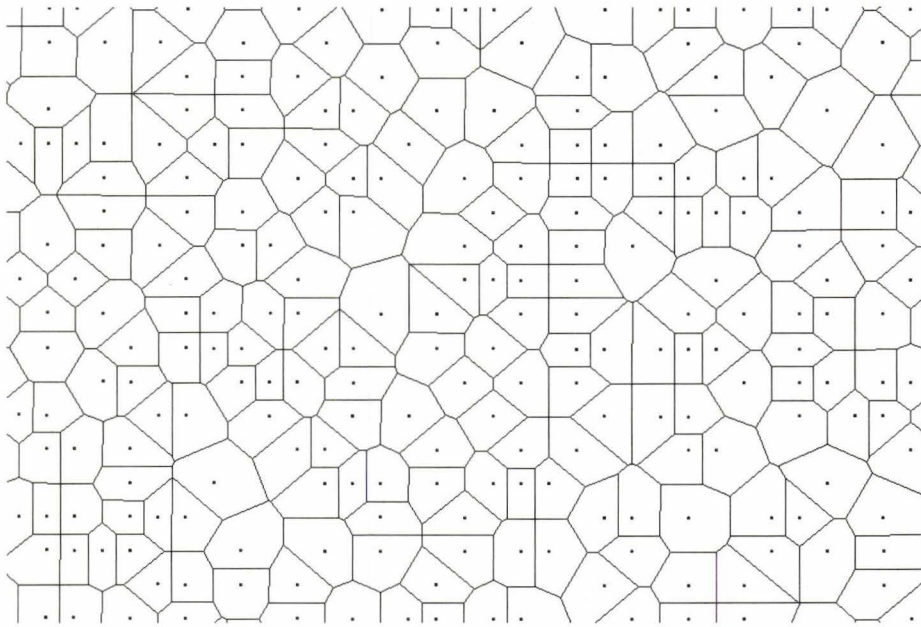


Figure 1.—Populating of the FIA data using “mid-point” algorithm (polygons would have boundaries equally distanced from all surrounding FIA plots).

boundaries, water resources, and road data. With this additional information the preliminary analysis was based on populating the FIA plots in circles of variable radii expanded around each plot but restricted by all the known boundaries and neighboring plot areas. Thus, the polygons around each plot were created by progressively expanding the radii until the area of the created polygons were equal to the areas represented by each plot according to the plot expansion factors established in the FIA program. Created in such a way, polygons were perfectly circular only in such instances where neighboring plots were not competing for common

areas. In all other instances, expansion of the initial circular polygons was restricted in directions of the competing plots and counties, roads, and water resources boundaries, which resulted in generally irregular shapes of the polygons, as can be observed in figure 2. Further improvement in the spatial population of the FIA data was obtained using additional information available from the Landsat TM satellite images for the expansion of the plots and computing the expanded areas only according to the actual areas of existing forests (fig. 3).

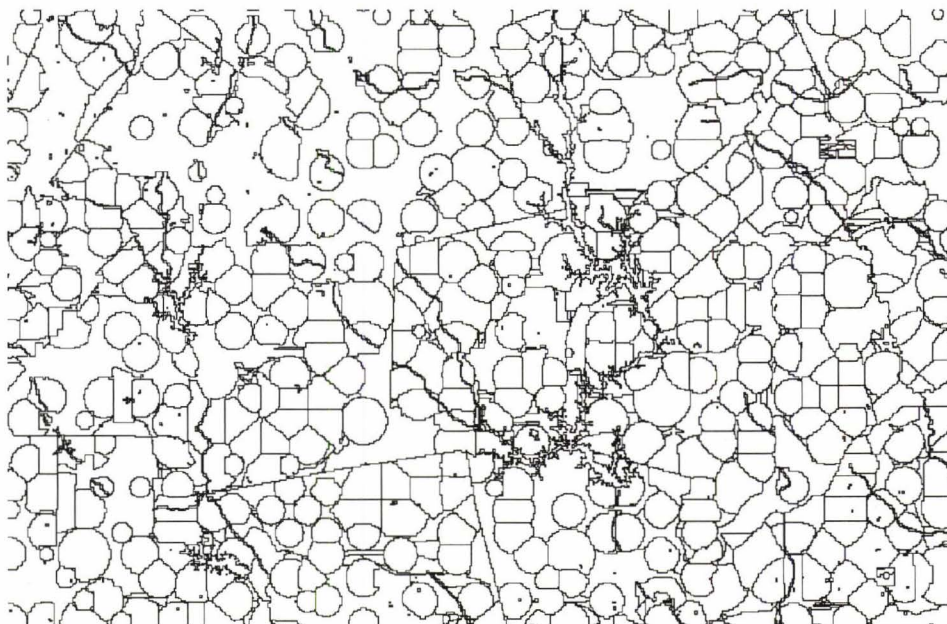


Figure 2.—Populating of the FIA data using “circle” algorithm. The polygons around each plot were created by expanding the radii according to the plot expansion factors of FIA plots. Circular polygons are restricted in directions of the competing plots and counties, roads, and water resources boundaries.



Figure 3.—Populating of the FIA data using forest areas from Landsat TM imagery.

SUSTAINABILITY ANALYSIS

For the sustainability analysis, we want to develop a methodology using Landsat TM, GPS, and GIS for fiber supply assessment on a short- and long-term basis. The main benefit of our study is expected to be in assessment and evaluation of various sensitivity analyses examining different levels of harvesting, regulatory constraints, and other methods of forest management. We run the simulations in annual time steps for 200-year periods. Such simulations produce useful information on sustainability of the current natural resources under various levels of utilization and statewide harvesting limits. We can also use them to assess impact of riparian zones, or buffers, around lakes, streams, rivers, and roads, as well as

maximum harvest constraints, and adjacency and green-up constraints.

Initial simulations included simplified scenarios with three species groups, five site index classes, two yield tables, and various management regimes. The species groups were natural softwoods, planted softwoods, and hardwoods. The yield tables were for planted loblolly pine (Harrison and Borders 1996) and upland oaks (Gingrich 1971). Different management regimes were based on forest management practices and simulation objectives.

The simulations were conducted assuming three harvesting levels: one approximately equal to the removals in the latest FIA report (Thompson 1998), one 20 percent below the latest FIA report, and one 20 percent above the latest FIA report. The results of the simulations suggested that the current level of harvesting was sustainable (fig. 4) but that a 20 percent increased harvesting level would not be sustainable (fig. 5).

It should be pointed out that the impact of intensively managed plantations has not been allowed for in this preliminary analysis although intensive silvicultural operations in pine plantations of the Southeastern United States can increase productivity levels two to four times more than the productivity of more traditionally managed stands (Borders and Bailey 2001). Within the past 10 years, hundreds of thousands of acres have been put into this type of high production situation. Furthermore, hundreds of thousands of acres of agricultural land have gone into pine plantation production through the Conservation Reserve Program (CRP). Typical pine plantations in this CRP program are over twice as productive as non-intensively managed plantations established on cutover forest land (Pienaar and

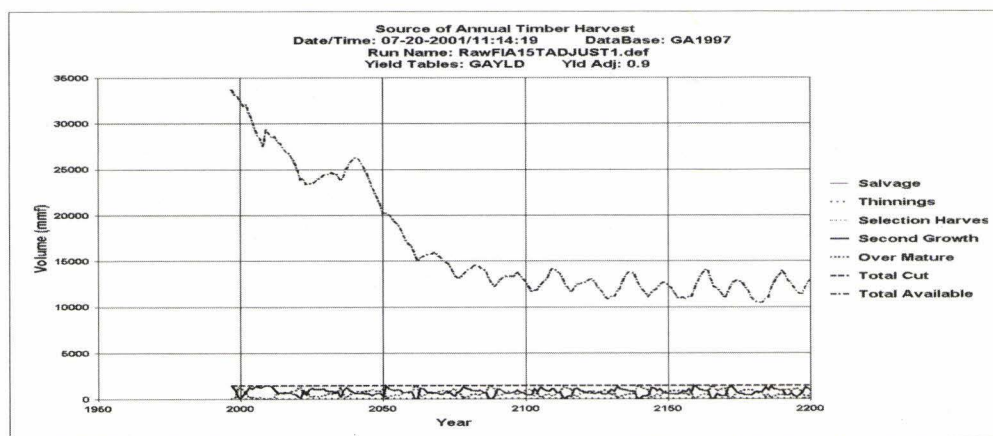


Figure 4.—Example results of the simulations—source of the annual timber harvest at current volume cut level—1.5 million cubic feet per year.

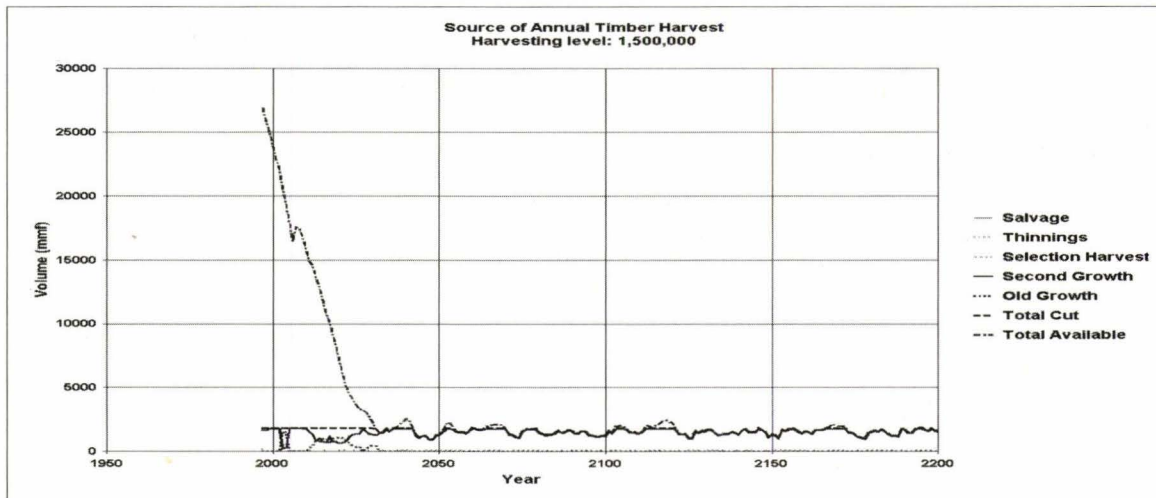


Figure 5.—Example results of the simulations—source of the annual timber harvest at 1.8 million cubic feet per year—20 percent higher than in 1997.

Rheney 1996). Together these two sources will contribute significant amounts to the available wood supply. Consequently, it is very important that we continue building additional growth and yield capability into the OPTIONS system so as to more realistically reflect the production of these important stand types.

CARBON BUDGET IN GEORGIA

In addition to carrying out sustainability studies as described above, we have developed spatially explicit estimates of the carbon and biomass pools for forests in Georgia (fig. 6). For this work we used individual biomass prediction equations available for various species in the Southeast. The equations were applied to each individual sample tree and above-ground woody stem and foliage biomass. Belowground biomass was estimated directly from aboveground biomass based on regression equations (Cairns and others 1997). Total biomass was defined as the sum of total tree woody, foliage, and root biomass. Biomass was converted to its carbon equivalent using a factor of 0.5 (Alexeyev and Birdsey 1998, Birdsey 1992) and expressed in Tg (10^{12} g). Such a partitioning of total biomass into total tree, foliage, and roots reflects differences in properties of tree components and in their role in the carbon cycle.

A stand is an aggregation of trees, and the stand biomass is defined as the sum of the biomass of the individual trees that make up the stand (Parresol 1999). According to this definition and the FIA database construction, we calculated tree, foliage, and root biomass per acre as a sum of the

biomass calculated with regression equations for each sampled tree multiplied by its tree expansion factor. Values per whole state, each broad class, and weighted averages were obtained using appropriate expansion factors from the plot level.

The details of our study were reported in Cieszewski and others (2001a). A preliminary analysis of biomass pools (reproduced here based on the work of Cieszewski and others (In prep.)) is shown in table 1. Based on this work, total tree biomass of Georgia forests in 1997 was 842 million dry tons while biomass of foliage and roots was 29 and 186 million dry tons, respectively. Total biomass of all forests (sum of total tree, foliage, and root biomass) was 1,057 million dry tons. Foliage makes up less than 3 percent and roots make up about 18 percent of total forest biomass of the State. Total tree biomass of hardwood species is 493 million dry tons, which is approximately 59 percent of the total biomass of all forests. However, hardwood species account for less than half (47%) of total foliage biomass (table 1). Since root biomass was calculated as a proportion of the total tree biomass, the proportion of hardwood root biomass relative to all species' root biomass is the same as the hardwood proportion of aboveground biomass (58%).

Through the GIS capabilities of OPTIONS, we can track the carbon budget spatially over time to produce projected carbon pools using a methodology similar to that described above and in Cieszewski and others (2001a). This capability will undoubtedly be useful in evaluating various management and policy decisions and their impact on carbon sequestration in forests.



Biomass density [t/ha]
Forested county area [x 1,000ha]
Biomass pool [x 10,000t]

Figure 6.—Biomass density [t/ha] by species groups on the plot level of resolution in Georgia. Numbers are biomass density [t/ha], area [x 1,000 ha], and carbon pool [x 10,000 t] on the county level of resolution, respectively.

Table 1.—Detailed analysis of dry biomass distribution calculated from FIADB

	<u>Tree</u>		<u>Foliage</u>		<u>Roots</u>		<u>Total</u>	
	mil. t	%	mil. t	%	mil. t	%	mil. t	%
Species groups								
Hardwood	515	59	14	47	112	58	641	59
Softwood	352	41	16	53	80	42	448	41
Forest type								
Evergreen	344	40	15	50	79	41	438	40
Deciduous	410	47	11	37	88	46	509	47
Mixed	113	13	4	13	25	13	142	13
Sum of component's		100		100		100		100
Biomass [mil. dry tones]	867	79	30	3	192	18	1,089	100

SUMMARY

The described study is designed to allow for simulations of various scenarios of forest management as well as to study the impact of regulatory constraints. As such, we are using and customizing the OPTIONS estate-planning model (by D.R Systems Inc.) for the Southeastern United States.

This large-scale long-term sustainability analysis involves many difficult technical aspects, some of which still pose unsolved problems. To date, progress in conceptualization of this project includes interim solutions for populating inventory plot data into realistic spatially explicit stand inventories, which can be used for simulation of long-term statewide simulation in forest resource management and utilization. Furthermore, we are continuing to add more stand-specific growth and yield capabilities, which will provide more realistic simulations.

Finally, we have shown that carbon budgets of forested areas can be estimated and projected using the OPTIONS estate-planning model. This capability will make this tool an essential component for evaluating management and policy impacts on future carbon pools.

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USE OF FOREST INVENTORY AND ANALYSIS INFORMATION IN WILDLIFE HABITAT MODELING: A PROCESS FOR LINKING MULTIPLE SCALES

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ABSTRACT.—We describe our collective efforts to develop and apply methods for using FIA data to model forest resources and wildlife habitat. Our work demonstrates how flexible regression techniques, such as generalized additive models, can be linked with spatially explicit environmental information for the mapping of forest type and structure. We illustrate how these maps of forest structure can be used to model wildlife habitat, focusing on the prediction of suitable habitat for cavity-nesting birds in forest systems in the Intermountain West.

Landscape data often have scale-specific resolutions and extents as well as thematic content due to methods of observation, making it difficult to scale measured responses of ecological systems either upwards or downwards. For example, use of satellite-derived data such as the National Oceanic and Atmospheric Administration's 1.1-km resolution Advanced Very High Resolution Radiometer (AVHRR) for mapping animal habitat automatically limits the scale of animal study to a 1.1-km resolution. Any gains in the ability to systematically map habitat over large spatial extents are offset by a loss of resolution relating back to the animal(s) of interest. Similarly, the kinds of ecological characteristics that plants often are associated with (e.g., microclimates, forest structure attributes) are frequently of such fine resolution that they cannot be systematically mapped or modeled over large spatial extents. As before, gains in the understanding of the ecological processes that may determine plant species distributions are offset by an inability to map these distributions over large spatial extents.

This limitation places serious constraints on the application of landscape theory to a wide range of forestry issues ranging from the development of spatially explicit, predictive maps of

forest resources for use in management to wildlife habitat modeling. The full exploration of landscape relationships requires spatially explicit depictions of habitat and other variables at fine resolutions over large spatial extents. Such depictions would allow for simultaneous exploration of relationships of variables at small spatial extents (e.g., canopy closure within forest stands) and over large landscapes (e.g., pattern of canopy closure within an ecoregion). Although it is possible to model structural attributes of habitats and vegetation on small regions using satellite imagery, the regional-scale focus of many cover-mapping efforts makes it difficult to build vegetation structure into cover maps. Current efforts provide good maps of broad cover classes at landscape levels (Homer and others 1997) but typically provide no information on the structure of the cover type or the spatial distribution of structure within the cover type. Recently, emphasis has been placed on linking forest data with satellite-based information not only to improve the efficiency of estimates of forest population totals, but also to produce regional maps of forest class and structure and to explore ecological relationships (Frescino and others 2001, Moisen 2000, Moisen and Edwards 1999, Moisen and Frescino in press). The accuracy of these types of map products is reasonably high (Edwards and others 1998, Frescino and others 2001).

Here we describe our collective efforts to develop and apply methods for using FIA data to model forest systems, focusing on the application of these FIA-based models for wildlife management. Our process requires two steps. The first step focuses on methods for modeling habitat that provide fine-grained estimations of forest habitat type and structure over

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large spatial extents. The second step is to use these representations of landscapes for modeling habitat use by terrestrial vertebrates at multiple scales. We illustrate how flexible regression techniques, like generalized additive models (GAM), can be linked with spatially explicit environmental information to map forest habitat structure. We next illustrate how the spatially explicit maps of forest structure can be used to model wildlife habitat, focusing on the prediction of suitable habitat for cavity-nesting birds in forest systems at landscape scales.

EXAMPLE APPLICATIONS

Study Area

The two example studies outlined here were conducted in the Uinta Mountains of northern Utah. The Uintas are characterized by an east-west orientation, and they have an approximate length of 241 km and a width of 48 to 64 km. Elevation ranges from ~1,700 to ~4,000 m. The area contains conspicuously deep, V-shaped canyons on the south side of the range and less pronounced canyons on the north side of the range. The distribution of vegetation in the Uinta Mountains is highly influenced by topographic position and geographic location. Lodgepole pine (*Pinus contorta*) is the dominant vegetation type, ranging from 1,700 to 3,000 m elevation. At elevations between 2,400 and 3,000 m, lodgepole is mixed with aspen (*Populus tremuloides*), with a few homogeneous aspen stands at lower elevations. As elevation increases, lodgepole forests are gradually replaced by spruce-fir (*Picea engelmannii*-*Abies lasiocarpa*) forest types and are frequently interspersed with large patches of wet and dry meadows. Other forest types include pinyon-juniper (*Pinus edulis*-*Juniperus osteosperma*) at lower elevations on the northeastern slope, Douglas-fir (*Pseudotsuga menziesii*) on steep, protected slopes, and ponderosa pine (*Pinus ponderosa*) forests on exposed slopes on the south side of the range (Cronquist and others 1972).

Modeling Forest Habitat Pattern and Structure

If a major objective of landscape modeling is to enhance understanding of relationships at multiple scales as a precursor for forest management, then methods for modeling scale-related ecological parameters are paramount. From a vegetation perspective, the principal question is how to accurately and efficiently model vegetation structure and

patterns at multiple scales. Recent advances in statistical modeling techniques (Hastie and Tibshirani 1990, Hastie and others 2001, McCullagh and Nelder 1989) and geographical tools, such as remote sensing and Geographical Information Systems (GIS), have increased the opportunities for the delineation and analysis of vegetation structure and pattern.

Readers are referred to Frescino (1998), Frescino and others (2001), Moisen (2000), Moisen and Edwards (1999), and Moisen and Frescino (in press) for details regarding the complexities of generating spatially explicit models of forest structure using FIA data. The process is necessarily complex, and only a short overview of work in the Uinta Mountains is presented below. In this study area, five response variables collected on FIA plots were modeled as functions of a wide variety of digitally available explanatory variables through GAMs (Frescino 1998, Frescino and others 2001). Response variables included binary forest and lodgepole presence, as well as continuous basal area, percent shrub cover, and snag density (table 1). A variety of explanatory variables were considered, including those related to topography, precipitation, geology, spatial position, as well as several from TM and AVHRR platforms (table 2). As noted above, the GAMs used for modeling are non-parametric extensions of the more commonly used generalized linear models (GLM). The GAM, like the GLM, uses a link function to establish a relationship between the mean of the response variable(s) and a smoothed function of the explanatory variable(s). The main attraction of GAMs for vegetation modeling is their ability to handle non-normal features in the data such as bimodality or asymmetry. GAMs are best described as data-driven rather than model-driven, such that the data determine the shape of the response curves rather than fitting a known function to the data. The major weakness of GAMs is the danger of overfitting the data (Austin and Meyers 1996).

For forest and lodgepole presence, a logit link was used to transform the mean of the response to a binomial scale. For the continuous variables (basal area, percent shrubs, snag density), a Poisson link was used to transform the data to the scale of the response. A loess smoothing function (see Venables and Ripley 1997 for description) was chosen to summarize the relationship between the predictors and the response. One limitation of smoothed functions obtained from GAMs is their inability to extrapolate outside the range of the data used to build the model. To handle this problem, values of the prediction and validation data sets that were

Table 1.—Summary of response variables for modeling forest attributes in the Uinta Mountains, Utah. See Frescino and others (2001) for additional details. P = proportion of model-building points defined as forest or lodgepole pine.

Forest attribute	Type	Description	Distribution
Forest presence	Binomial	>10% tree cover	P = 0.77
Lodgepole pine presence	Binomial	Majority of forest cover	P = 0.31
Basal area (m ² /ha)	Continuous	Area of trees at 1.37 m basal ht. (Trees > 2.5 cm d.b.h.)	Range: 0 to 70 Median: 16
Shrubs (%)	Continuous	Sum of total cover from upper, middle, and lower layers	Range: 0 to 92 Median: 15
Snag density	Continuous	Total salvable and non-salvable (Snags > 10.2 cm d.b.h.)	Range: 0 to 248 Median: 5

Table 2.—Summary of explanatory variables used to model forest attributes in the Uinta Mountains, Utah. See Frescino and others (2001) for additional details.

Variable	Type	Resolution	Source
Elevation (m)	Continuous	90 m	DMA
Aspect (°)			Derived from DMA
	Continuous	90 m	Relative annual solar radiation (Swift 1976)
	Discrete	90 m	9 categories
	Continuous	90 m	Radiation/wetness index (Roberts and Cooper 1989)
Slope (%)	Continuous	90 m	Derived from DMA
Precipitation	Continuous	90 m	Downscaled from PRISM; yearly precipitation climate maps
Geology			Hintze (1980)
	Discrete	1:500,000	Timeframe (1-Precambrian, 2-Mississippian to Eocene, 3-Alluvium)
	Discrete	1:500,000	Nutrients (1-sandstone and limestone, 2-sedimentary, 3-alluvial)
	Discrete	1:500,000	Rock Type (1-sedimentary, 2-alluvial)
Easting	Continuous	-	UTM Easting coordinates
Northing	Continuous	-	UTM Northing coordinates
District	Discrete	-	7 National Forest Ranger Districts
TM-classified	Discrete	90 m	GAP Analysis (Homer and others 1997)
AVHRR	Continuous	1,000 m	NOAA (June 1990)
TM			Landsat TM (June 1990/August 1991)
	Continuous	30 m	TM Band 3 (Red)
	Continuous	30 m	TM Band 4 (Near-infrared)
	Continuous	30 m	TM Band 5 (Mid-infrared)

outside the range of the model-building data set were assigned the maximum/minimum value of the respective variable in the data set.

The functional relationships between each explanatory variable and the respective response variables were analyzed for potential parametric fits following guidelines in Hastie and Tibshirani (1990) and Yee and Mitchell (1991). If a potential parametric fit existed, piecewise and second- and third-order polynomial functions were fit to the data and assessed based on the relative degree of change to the residual deviance (Cressie 1991). All explanatory variables, including all potential parametric fits, were run through a stepwise procedure to determine the best-fit model for prediction (see Chambers and Hastie 1992) using Akaike's Information Criterion (AIC). A percent deviance reduction (D^2) was also calculated for each model, representing the percent of deviance explained by the respective model (Yee and Mitchell 1991). Once the model fits were derived (see Frescino and others 2001, tables 3 and 4), the model was applied to all the explanatory digital layers (table 2) and predictive map surfaces generated. The result was a series of predictive maps of forest attributes having fine resolution (~ 0.8 ha) and covering large spatial extents (>1 million ha) (fig. 1).

Accuracy of the models predicting forest and lodgepole presence was high, ranging from 86 to 80 percent,

respectively. Sixty-seven percent of the basal area validation points fell within ± 15 percent ($11.5 \text{ m}^2/\text{ha}$) of the true value, 75 percent of the shrub density validation points fell within ± 15 percent of the true cover, but only 54 percent of the points fell within ± 15 percent of the true snag count.

Modeling Cavity Bird Nesting Habitat in Forested Systems

Once the maps of forest attributes are generated, the next step is to generate models of bird presence based partly on the spatially explicit forest maps. As an example in the Uinta Mountains, habitat associations based on landscape patterns were modeled for four species of cavity-nesting birds nesting in aspen (Lawler 1999; Lawler and Edwards, in press). These species include red-naped sapsuckers (*Sphyrapicus nuchalis*), northern flickers (*Colaptes auratus*), tree swallows (*Tachycineta bicolor*), and mountain chickadees (*Parus gambeli*).

Habitat models were built for each of the four species using classification trees (Breiman and others 1984, Venables and Ripley 1997). Classification trees are a flexible and simple tool for modeling complex ecological relationships (De'ath and Fabricius 2000). Classification trees work by recursive partitioning of the data into smaller and more homogeneous groups with respect to the response variable. Each split is

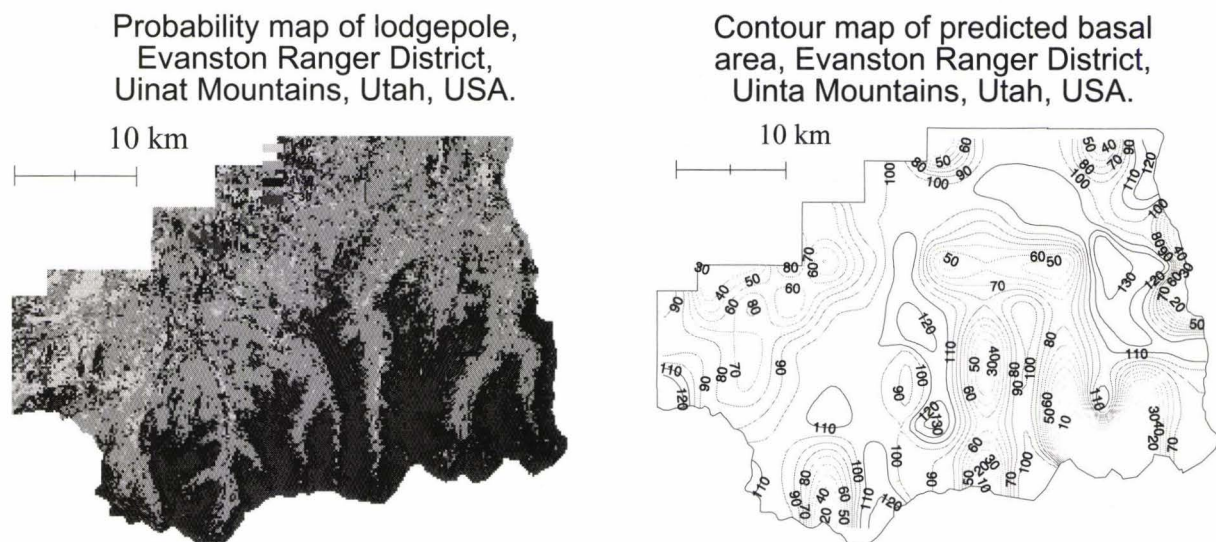


Figure 1.—Example maps of nominal (lodgepole presence) and continuous (basal area) responses generated for a $\sim 100,000$ -ha region of the Uinta Mountains, Utah (from Frescino 1998).

made by the explanatory variable and the point along the distribution of that variable that best divides the data. See De'ath and Fabricius (2000) and Lawler and Edwards (in press) for a more thorough discussion of the use of classification trees in ecological modeling.

The four species models included a number of variables pertaining to the amount and configuration of forest and open area (fig. 2). Spatially explicit predictions for each of the four species were produced from these models (fig. 3). The spatial configuration of forest that was predicted as suitable nesting habitat differed among the four species, and the models varied in their ability to correctly predict nests at the new sites (Lawler and Edwards, in press). The northern flicker model was the most accurate (84 percent of nests correctly classified). The red-naped sapsucker and tree swallow models were also relatively accurate (80 percent and 75 percent of the nests correctly classified, respectively). The mountain chickadee model was far less accurate, correctly predicting only 50 percent of the nests at the test sites. These estimates are within ranges of accuracy reported elsewhere (Edwards and others 1996).

CART model Red-naped sapsucker

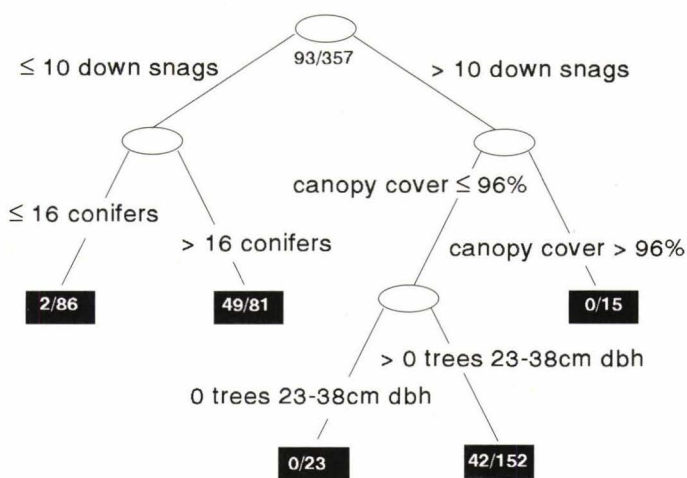


Figure 2.—Classification and regression tree model predicting nesting habitat for red-naped sapsuckers. Models for the other species were similar in structure, varying only in the predictor variables and tree complexity (see Lawler and Edwards, in press).

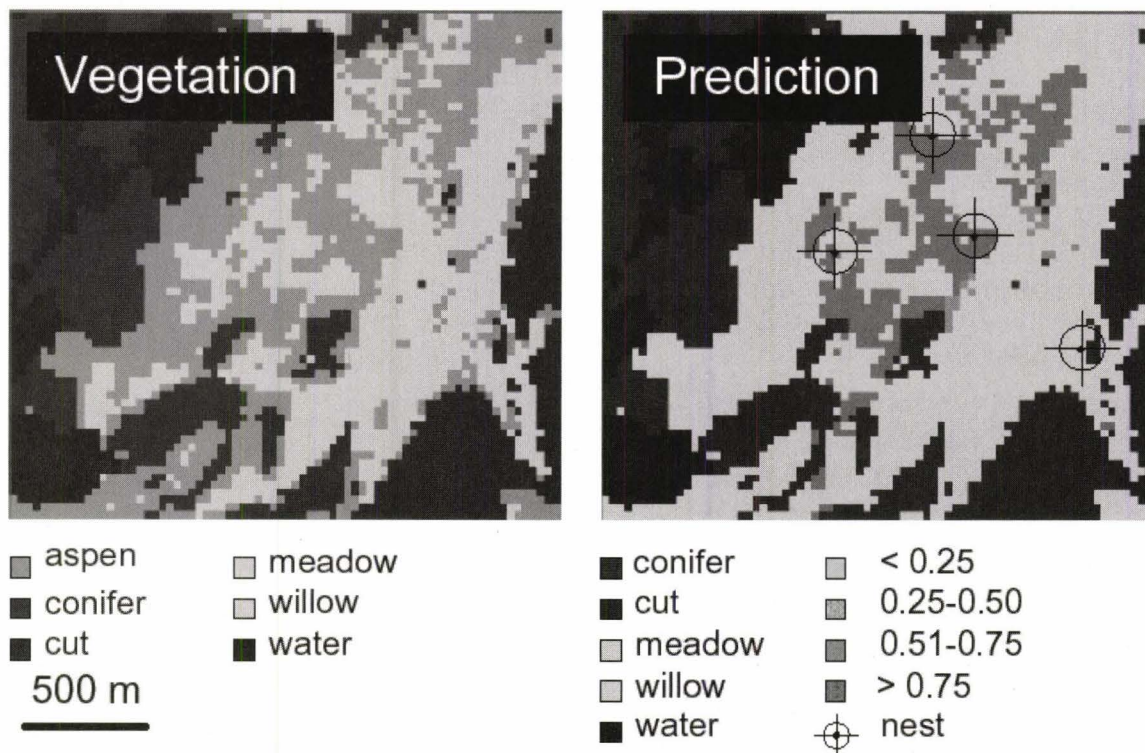


Figure 3.—Vegetation and spatially explicit prediction maps for northern flicker nesting habitat. Medium gray in the vegetation map represents suitable nesting habitat and is based on classical WHR approaches (see text). Note how the amount and distribution of gray are reduced under the refined vegetation models, which then are incorporated in the wildlife models as described in the text. Nests are represented as circles with crosshairs.

DISCUSSION

The ability to create spatially explicit depictions of vegetation type and structure is dependent, in part, on the flexibility and capability of the models used to predict vegetation characteristics. GAMs, in contrast to some analytical procedures (e.g., ordination and linear regression models), do not make *a priori* assumptions about underlying relationships, thus allowing the data to drive the fit of the model instead of the model driving the data. The graphical nature of GAMs also allows a visualization of the additive contribution of each variable to the respective response using smoothed functions. One limitation of GAMs is the uncertainty associated with extrapolation of the smoothed functions, particularly at the tails of the distribution. As suggested by Hastie and Tibshirani (1990) and Yee and Mitchell (1991), parametric functions were to the model whenever statistically allowable, thus constraining the behavior of the functions in the extreme ranges of the data. See Moisen and Frescino (in press) for a comparison of alternative modeling techniques for predictive mapping applications.

Once the vegetation type and structure are modeled, the resultant maps can be linked with wildlife models and used to create predictive maps. Although predictive models based on landscape patterns may prove to be a promising technique in light of their ease of use and relative accuracy, like all models they have distinct shortcomings. The ability to build such models depends on having access to remotely sensed data. Fortunately, remotely sensed data are becoming not only more diverse, but also more widely available. Because the field of landscape ecology is relatively young, associations between given species and landscape patterns are not as prevalent in the literature (Karl and others 1999) as are associations with the composition and structure of vegetation at relatively fine spatial scales (e.g., Cody 1985). Thus, many of the basic habitat associations related to landscape patterns will need to be determined in the field for the first time.

Selecting the scales at which to measure landscape patterns is difficult when modeling several different species. Different species are likely to respond to their environment at different spatial scales (Wiens 1989). Models built solely at coarse spatial scales and using only vegetation type are likely to be less accurate when fine-scale associations with structural attributes are strong. Our approach, which employs

techniques capable of modeling fine-scale attributes (e.g., canopy closure, stem density) at fine resolutions, overcomes this issue and generally increases model predictive capabilities. The use of new, more flexible modeling techniques such as classification trees (De'ath and Fabricius 2000) may further improve the predictive capability of models of forest resources, and the wildlife dependent on these resources, as well as the ease of model building and interpretation. Although our results indicate that our approach may not work equally well for all species, we found that when tested and refined, models that rely on landscape patterns derived from FIA data may provide a reliable alternative to traditional wildlife models that require the collection of habitat data in the field and have no spatial resolution.

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USING SPECIFIC VOLUME INCREMENT (SVI) FOR QUANTIFYING GROWTH RESPONSES IN TREES—THEORETICAL AND PRACTICAL CONSIDERATIONS

Eddie Bevilacqua¹

ABSTRACT.—Comparative analysis of growth responses among trees following natural or anthropogenic disturbances is often confounded when comparing trees of different size because of the high correlation between growth and initial tree size: large trees tend to have higher absolute grow rates. Relative growth rate (RGR) may not be the most suitable size-dependent measure of growth when studying larger trees since RGR is also highly correlated with tree size: larger trees tend to have lower RGR. This article demonstrates that specific volume increment is a more appropriate size-dependent measure of growth based on theoretical considerations and on empirical evidence with competition indices.

In research investigations based on observational studies, the investigator is forced to deal with the constraint of limited local control of experimental units relative to comparative experiments. This is particularly true in forest growth studies that are designed to investigate the growth response of trees following disturbance or changing levels of resource availability. The lack of experimental control is often the consequence of dealing with trees of different size. The difficulty generally arises from the tendency of larger trees to accumulate more bole growth than smaller trees.

Possible solutions to these experimental problems are to incorporate a covariate, such as initial tree size, into the analysis, or to redefine the response variable to a measure of relative growth, that is, measure new growth relative to initial size, such as relative growth rate.

Relative growth rate (RGR) is a term originating from early studies in whole plant growth analysis (Blackman 1919; Briggs and others 1920a,b). The original premise of RGR was based on the assumption that the initial size of plant (W) has some physiological contribution or link to any new biomass produced. Therefore, when plants had ample resources needed for growth, they would grow at a constant exponential

rate, implying a constant RGR. This facilitated the comparison of plant growth for plants of different initial sizes. When resource levels change or become limiting, the RGR of a plant should decrease.

Comparisons between plants having different RGR could then be assessed by decomposing RGR into two physiological components, the photosynthetic efficiency (PE) and photosynthetic capacity (PC) (see equation 1). Photosynthetic efficiency represents the amount of plant growth per unit leaf area, whereas photosynthetic capacity represents the relative amount of photosynthetic material per unit of plant weight.

$$\begin{array}{rclcl} \text{RGR} & = & \text{PE} & * & \text{PC} \quad (1) \\ [(dW/dt) / W] & = & [(dW/dt) / A] & * & [A / W] \end{array}$$

where W = total initial weight of plant, A = total leaf area of plant, and t = time

Schwinning (1996) further extended the concept of whole plant growth analysis and the decomposition of relative growth rates (i.e., equation 1) to examine the mode of competition, size dependence of growth, and their interdependence on resource uptake.

The forestry research community adopted the whole plant growth analysis to assess how silvicultural activities and environmental stresses influence tree growth. However, early researchers had difficulty measuring W (total weight of a tree, including roots) and would often substitute other measures of

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tree size, such as aboveground weight, bole volume, or d.b.h. for W. Within this context, Waring and others (1980), when substituting bole volume for plant weight, considered the PE term—stem growth per unit leaf area—as a measure of tree vigor.

The limitation of using RGR in forestry growth studies, particularly in studies focusing on the bole growth in a tree, is the predictable change in RGR with tree age (fig. 1). This minimizes the utility of using RGR for comparing the effects of silvicultural activities or environmental influences over extended periods of time on trees of different sizes. Larger trees generally accumulate more new bole growth in absolute amounts. As trees age, the quantity of new bole growth becomes a smaller fraction of the underlying initial bole volume—i.e., decreasing RGR. The volume of the bole is the cumulative growth of the tree stem over its entire life, and as a tree ages, the volume of the bole has a decreasing physiological function with respect to any new bole growth. As trees become larger, the function of the main bole shifts from being an assemblage of pipes conducting water from the roots to the foliage to providing the mechanical support allowing the tree to reach greater heights. Only a portion of

the bole volume, which is defined as sapwood, is used to conduct water. Morataya and others (1999) considered sapwood volume as a linkage between initial bole size and new bole growth. However, measuring or estimating sapwood volume in a standing tree can be quite difficult because of its very dynamic nature.

In their detailed analysis of stem growth, Duff and Nolan (1957) proposed a relative measure of internodal growth they termed Specific Increment in Volume (SIV), which measured the amount of new volume growth per unit of cambial surface area. They reasoned that the cambial surface contained all the new xylem cells that would eventually form the bole of a tree, as well as the respiratory surface for all new bole growth. They demonstrated mathematically that the SIV could be estimated as the average width of an annual ring within an internode. The use of volume growth per unit cambial surface area was later extended from its measurement within a single internode to a look at the whole bole of a tree. The volume of new bole growth is expressed relative to the bole surface area, which is used to estimate the total amount of cambial surface area over the entire bole. This measurement of size-dependent growth at the tree level was termed the Specific Volume Increment (SVI).

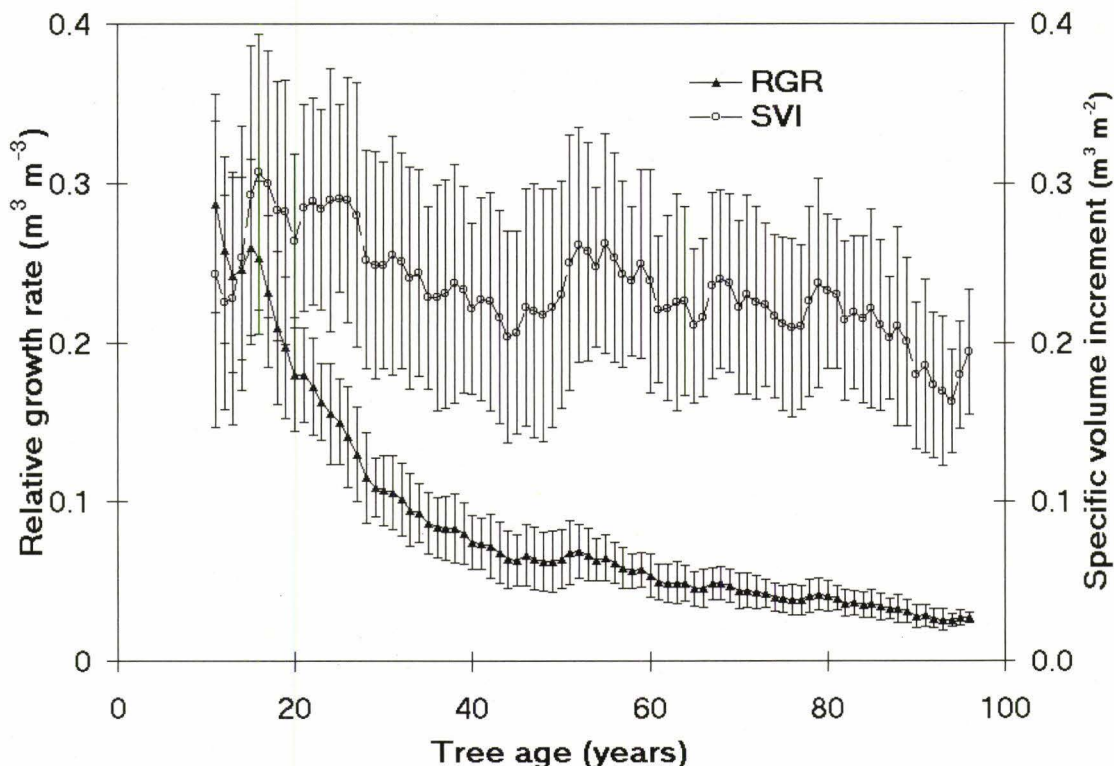


Figure 1—Age-related variation in relative growth rate (RGR) and specific volume increment (SVI) of the main stem for 38 emergent and dominant white pine trees calculated on a yearly basis. The data were taken from the control group only, so as to not confound the age-related trend with the release treatment effect. Vertical bars represent one unit of standard deviation about the mean.

Unlike RGR, which decreases with tree age, SVI remains relatively constant for an extended period of time as trees age. Figure 1 illustrates that early in a tree's life, RGR and SVI of the main stem have relatively similar mean values and levels of variation. However, as trees age, there is a rapid decline in both the mean and variance of RGR. This observation supports the hypothesis that the increasing size of the non-productive inner bole in large trees has a greater influence on RGR than differences in annual increment.

The use of RGR as a measure of tree vigor would suggest that all trees rapidly lose vigor with age, regardless of their immediate environment or canopy position. In contrast to this, the mean value of SVI displays a much more gradual decline with age, albeit with a large degree of variability among trees. The large variability in SVI would suggest that it might be more sensitive to changes in the growth response of trees to environmental stimuli and that it might better reflect the relative growth variation among trees that are the result of differences in the local level of resource availability immediately surrounding them.

Based on these theoretical considerations, there are three benefits of using SVI over RGR in studies designed to compare the effects of natural or anthropogenic disturbances on the growth of trees of varying size:

1. Using initial bole surface area to represent the amount of cambial tissue implies a physiological link to new bole growth, whereas initial bole volume does not.
2. SVI is less correlated with tree age, allowing for a more valid comparison in relative growth for trees of different ages.
3. SVI is more variable than RGR across a greater range of ages, suggesting it may be easier to identify the influence of natural or anthropogenic disturbances on tree growth.

To confirm the benefit of using SVI over RGR, empirical evidence was collected from a study designed to investigate the effects of competition release on the growth of mature eastern white pine (*Pinus strobus* L.) trees.

METHODS AND MATERIALS

Field Site

Trees selected from within the Cartier Lake Silvicultural Area within the Petawawa Research Forest (PRF), Chalk River, Ontario were used in this study. The PRF is located on the eastern boundary of Algonquin Provincial Park, Renfrew County, Ontario (45°59'N 77°26'W). The climate is characterized by short warm summers and cold winters, with an average annual temperature of 4.3 °C. The average length of the growing season is 116 frost-free days. Precipitation averages 832.1 mm per year, with 55 percent falling between April and September.

This study area had been cut in 1971 to varying levels of residual basal area. The aim of that earlier study was to improve the growth and yield of white pine for saw log production and "at providing the option of long-term uniform shelterwood management" (Stiell 1984). The cutting treatments consisted of the removal of all species of pulpwood size (9 cm d.b.h.) and larger, except for the understory pine and spruce. The main species removed were trembling and largetooth aspen and white birch. Thus, the residual stands in the treated areas were mainly composed of white pine, with a minor component of red pine and white spruce. The intensity of the cutting treatment varied depending on the pre-treatment level of white pine in the stand. Part of the area was left as an uncut control. Initial cutting treatments are described in more detail by Stiell (1984). Because of the ongoing study, restrictions were placed on which trees could be selected for this research; namely, trees were selected from a distance of at least two-tree lengths from existing permanent sample plots.

Tree Selection and Stem Analysis

Trees selected for detailed stem analysis were chosen from within the six treatments outlined in Stiell's (1984) experiment. To analyze the variation in tree response due to canopy position, trees were further stratified into three dominance classes: emergent (greater than 3 m above average canopy height), dominant/co-dominant (within +/- 3 m of average canopy height), and intermediate (greater than 3 m below

Table 1.—Number of sample trees selected based on cutting treatment, pine density before cutting, and dominance class

Cutting treatment	Pine density	Dominance class			TOTAL
		Emergent	Dominant	Intermediate	
Control	Low	2	2	2	6
Control	Medium	9	11	4	24
Control	High	4	10	1	15
Released	Low	4	10	2	16
Released	Medium	5	7	1	13
Released	High	4	8	2	14
TOTAL		28	48	12	88

average canopy height). A total of 88 trees were selected.

Table 1 shows the distribution of selected trees based on cutting treatment, pine density, and tree dominance class.

The main stem of each tree was then divided into 20 sections, with the base of each section taken at the following heights: 0.15 m (stump), 1.37 m (d.b.h.), and at 5-percent intervals from 10 to 95 percent of total tree height. A disk was removed from the base of each section to conduct detailed stem analysis on each subject tree back in the lab.

Stem disks were stored in cold rooms at 5 °C for up to 8 months at the Petawawa Research Forest and the Faculty of Forestry, University of Toronto. They were then allowed to air dry for a minimum of 2 months before being prepared for tree-ring measurements. Disk preparation involved sanding the bottom surface of each disk, first with 60- to 80-grit sand paper, followed by light sanding with 100-grit sand paper.

On each disk, tree ring widths were measured along four radii taken at 90° angles from each other using the Tree Ring Increment Measurement (TRIM) system initially developed by Fayle and McIver (1986). The TRIM system was updated by interfacing the SONY electronic ruler in an IBM compatible PC using a LOTUS 1-2-3™ spreadsheet developed by the Miller (unpublished 1990). The average of the four ring widths was used to reconstruct the yearly cumulative diameter growth of each stem section and then compute the yearly volume and surface area for the entire tree bole using techniques described in Avery and Burkhart (1994).

Growth Estimation

Using the same principles as outlined in Causton and Venus (1981) and Hunt (1982), continuous functions—i.e., polynomial equations—of the bole surface area (SA, equation 2) and volume (V, equation 3) for each tree over time since treatment. Third-order polynomial equations were selected based on their better overall goodness of fit (i.e., higher coefficient of determination and lower root mean squared error) with the data.

$$SA = f(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 \quad (2)$$

$$V = g(t) = b_0 + b_1 t + b_2 t^2 + b_3 t^3 \quad (3)$$

where SA = bole surface area, V = bole volume, t = time, $a_0, \dots, a_3, b_0, \dots, b_3$ = parameters to be estimated

RGR and SVI can be calculated at any point in time using equations 4 and 5, respectively,

$$RGR = (dV/dt) / V = \dot{g}(t) / g(t) \quad (4)$$

$$SVI = (dV/dt) / SA = \dot{g}(t) / f(t) \quad (5)$$

Size-related Growth and Competition

Once the subject trees were identified, the size and location of potential competitors were determined using a BAF=2 (metric) prism, using each subject tree as the center point of prism sweep, following the procedures outlined by Spurr (1962). For each competitor, its azimuth and distance from the subject tree was recorded, as well as its species, diameter at breast height (d.b.h.) and height class relative to the subject tree's height (-1 = more than 3 m shorter than the subject tree, 0 = within +/- 3 m of subject tree, and +1 = more than 3 m taller than the subject tree).

Three distance-independent and eight distance-dependent competition indices were calculated for each subject tree for each year from 1971 to 1994 and correlated with the SVI. The distance-independent (DI) indices included number of competitors (CI01), cumulative squared relative diameter of competitors, and cumulative diameter of competitors (CI03). Distance-dependent indices included Weiner's (1984) neighbourhood interference (CI04), Spurr's (1962) point density index (CI05), cumulative horizontal angle (Rouvinen and Kuuluvainen 1997) (CI06), and Hegyi's (1974) size-distance ratio (CI07). Two of the indices included variations of the crown overlap (CO) index type. Since there is no available information on open growth crown width for white pine of different sizes, the radius of the influence zone for each tree was directly related to the tree's diameter using the same approach as Tome and Burkhart (1989). The radius of zone of influence was expressed as a linear function of tree d.b.h. from 0.1 to 1.0 times d.b.h. in steps of 0.1. The function that produced the best empirical correlation between size-related growth and competition was selected. One index was based on the cumulative overlap between zones of influences (CI08), while the other weighted the overlap by the relative size of the competitor to the subject tree (CI09).

The final two indices tested were based on area potential available (APA). Since APA increases with decreasing competition, the inverse of APA was used to be consistent with the

other competition indices. One of the APA indices tested was Brown's (1965) original calculation, bisecting the distance between subject and each competitor at right angles and forming a polygon around the subject tree (CI10). The other applied Moore and others' (1973) weighted division of distance between trees based on relative tree size (CI11).

RGR and SVI were regressed against the 11 competition indices using equation 6 and employing data from the last 5 years of measurement (1990-94). Relationships between the two size-dependent measures of growth (i.e., RGR and SVI) and the competition indices were tested using the following model

$$\ln(Y) = \beta_0 + \beta_1 \cdot CI \quad (6)$$

where Y is either RGR or SVI, CI is one of the competition indices, and b_0 and b_1 are parameters to be estimated.

RESULTS

The results from the regression equations in table 2 demonstrate that all competition indices explain a larger proportion of the variation in $\ln(\text{SVI})$ (i.e., higher R^2) as compared to $\ln(\text{RGR})$. R^2 values for $\ln(\text{RGR})$ are comparable to the level of correlation Peterson and Squiers (1995) obtained when they

Table 2.—Parameter estimates and regression statistics from regression analysis relating two size-dependent stem growth measurements, (i) relative growth rate (RGR) and (ii) specific volume increment (SVI) of white pine trees to competition indices

Competition Index ^b	Y = RGR ^a				Y = SVI			
	β_0	β_1	RMSE ^c	R ² ^d	β_0	β_1	RMSE	R ²
CI01	-3.111	-0.0287	0.3365	0.1250	-0.973	-0.0494	0.4333	0.2040
CI02	-3.381	-0.0084	0.3337	0.1394	-1.288	-0.0217	0.3376	0.5169
CI03	-3.094	-0.0010	0.3346	0.1349	-1.062	-0.0014	0.4454	0.1590
CI04	-3.138	-0.0054	0.3326	0.1450	-0.973	-0.0098	0.4155	0.2681
CI05	-3.310	-0.0002	0.3282	0.1678	-1.329	-0.0003	0.4189	0.2561
CI06	-3.241	-0.0143	0.3293	0.1619	-0.982	-0.0345	0.3373	0.5178
CI07	-3.380	-0.0054	0.3253	0.1824	-1.320	-0.0129	0.3165	0.5753
CI08	-3.105	-0.1009	0.3216	0.2009	-0.867	-0.1953	0.3722	0.4129
CI09	-3.316	-0.0461	0.3258	0.1800	-1.196	-0.1050	0.3398	0.5104
CI10	-3.494	-0.8585	0.3570	0.0153	-1.562	-2.5281	0.4677	0.0727
CI11	-3.469	-0.8699	0.3365	0.1251	-1.530	-2.1197	0.3738	0.4076

^a Model: $\ln(Y) = \beta_0 + \beta_1(CI)$.

^b see Methods and Materials for definitions of competition indices.

^c RMSE = Root mean squared error.

^d R² = Coefficient of determination.

analyzed the relationship between relative diameter growth rate and competitive interference in white pine. This strong correlation between $\ln(\text{SVI})$ and competitive interference supports the hypothesis that SVI is a more appropriate measure of size-dependent growth compared to RGR when investigating the influence of competitive interference on the growth of older trees.

SVI is negatively correlated with the level of cumulative competitive interference of all species of competitors, and more than half of the variation in SVI could be accounted for by competitive interference alone (table 2). A comparison of the efficacy of the competition indices shows that the regression models from this study have comparable levels of correlation to that found in the literature.

PRACTICAL IMPLICATIONS

The estimation of SVI at the individual tree level does not require additional data collection procedures, such as complete stem analysis. Given simple allometric relationships for both bole volume and surface area as functions of tree d.b.h., height, and form, SVI can be estimated over time through simple differentiation over time.

$$V = FD^2H \quad (7)$$

$$SA = kDH \quad (8)$$

$$\text{SVI} = (D/k) \cdot (dF/dt) + (2F/k) \cdot (dD/dt) + FD/(Hk) \cdot (dH/dt) \quad (9)$$

where V = bole volume, SA = bole surface area, D = tree d.b.h., H = tree height, F = tree form, t = time, k = constant, SVI = specific volume increment.

Can we extend the use of SVI as a size-dependent measurement of growth from the individual tree to the stand level? At the stand level, stand growth is already qualified using some measure of stand occupancy or density, such as variable density yield curves. The density variable is one method of quantifying the initial growing stock in a stand. In most of these growth models, density is expressed as either the number of trees or basal area per unit area. These measures are often used because of their simplicity in calculation rather than their direct biological compatibility with growth. The total bole surface area of all trees per unit area (stand bole area) should provide a more biologically meaningful measure of stand occupancy based on the premise that it quantifies the amount of cambial tissue from which new wood material initiates.

Lexen (1943) originally proposed using stand bole area as a measure of stand density when studying ponderosa pine stands. Mulloy (1944) later investigated the differences between using stand bole area and Reineke's (1933) Stand Density Index in red (*Pinus resinosa* Ait.) and white pine (*P. strobus* L.) stands, finding both measures of density to be similar. This would suggest that stand bole area might be the more appropriate measure of stand occupancy, particularly in process-based models of forest growth, based on the physiological link between cambial surface area and new xylem growth.

An additional benefit of using stand bole area is that the calculation of this variable will not require the collection of any additional forest inventory data. A simple allometric relationship predicting tree bole area using d.b.h. and height can be employed with a stand table to estimate stand bole area. Further research into the use of bole area as a measure of stand occupancy is needed.

CONCLUSIONS

To conduct valid comparisons between present and past growth rates in trees or stands, there is a need to express periodic growth relative to the initial size of a tree or growing stock in a stand (i.e., size-dependent growth). Using initial bole volume or stand yield may be inadequate because of the lack of a physiological link between any new growth and these initial size variables. It is being recommended the initial bole surface area (either at the tree or stand level) again be studied as possible measures of initial tree or stand size, particularly because of the strong physiological link between the amount of cambial material and periodic bole growth.

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DEVELOPMENT OF A STAND DENSITY INDEX EQUATION FOR SLASH PINE STANDS

Paul F. Doruska¹

ABSTRACT.—Stand density index (SDI) is commonly used as the basis for density management guides for even-aged forest stands. Many tree species follow the same self-thinning trajectory, allowing for the use of stand density index in such guides. Slash pine (*Pinus elliottii* Englem.) has been shown to depart from the self-thinning trajectory exhibited by other tree species. However, slash pine stands do follow a self-thinning trajectory. A stand density index equation for slash pine is herein developed. Although different from the form generally accepted for other species, the new equation can still be used to estimate relative densities of varying slash pine stands, and it may potentially serve as the basis for a stand density index-based management guide for slash pine plantations.

L.H. Reineke first introduced his concept of stand density index in the early 1930s. Reineke (1933) reported that even-aged stands of a variety of species followed the same size-density relationship or self-thinning pattern. Once this pattern was quantified, a relative measure of stand density, called stand density index (SDI), was created. Stands with the same SDI are of the same relative density regardless of the individual ages or sizes (quadratic mean diameter) of the stands (see also Avery and Burkhart 2001).

SDI has been used for a variety of purposes for a multitude of species since the original work of Reineke (1933). Most of this work has centered on the creation and subsequent use of density management diagrams. Stand managers can use density management diagrams to determine the relative density of a stand, compare relative densities between stands, and schedule harvesting (partial or final) activities based on the SDI. The goal of SDI-based management is to maintain a given stand at a target density or within the levels (thresholds) of two target densities. For example, SDI can be used to identify the self-thinning threshold and the minimum site occupancy threshold for loblolly pine (see Dean and Baldwin 1993).

Drew and Flewelling (1979) introduced the concept of density management diagrams with their work on Douglas-fir

(*Pseudotsuga menziesii* [Mirb.] Franco). McCarter and Long (1986) extended the concept of density management diagrams to lodgepole pine (*Pinus contorta* Dougl. ex Loud.) and incorporated height of dominants and codominants into the guide, allowing for the approximate age of the harvesting activities to be determined as long as the stand's site index is known. SDI-based management research on lodgepole pine continues as evidenced by Whitehead and others (2001) and their work on using SDI-based management to control beetle outbreaks. Newton and Weetman (1994) developed an SDI-based density management tool for black spruce (*Picea mariana* Mill.), and Newton (1998) reported a computerized version for black spruce. Dean and Baldwin (1993) developed a density management diagram for loblolly pine, as did Williams (1994, 1996), who added yield information to the diagrams. Doruska and Nolen (1999) introduced a spreadsheet version of SDI-based density management for loblolly pine plantations; their use of a spreadsheet allowed for thinned and nonthinned stands to grow and develop differently within an SDI-based management scenario.

Reineke (1933) noted that slash pine (*Pinus elliottii* Englem.) and longleaf pine (*Pinus palustris* Mill.) departed from the self-thinning pattern of most other species he examined. Therefore, the slope of the size-density relationship is different for these two species. SDI-based research involving these species has been sparse. Dean and Jokela (1992) developed a management guide for slash pine based on the concept of annual growth potential as opposed to SDI.

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This paper traces the development of an SDI equation for slash pine. The equation developed herein can then be used to compare relative densities of slash pine stands and potentially serve as the basis for density management diagrams or spreadsheets for slash pine plantation management.

THE DATA

A large, anonymous landowner in the Southeastern U.S. granted access to its slash pine inventory data. The data obtained and used were from the southwest Gulf Coastal Plain. A total of 1,638 stand inventories were used, with each stand inventory providing the following information: trees per acre, quadratic mean diameter (in.) and thinning status. Table 1 contains summary statistics of these data taken as a whole (combined data) and separately (nonthinned and thinned data).

METHODS

The following equational form was fit to the nonthinned, thinned, and combined slash pine data sets, respectively:

$$\text{Log}_{10}(N_i) = \beta_0 + \beta_1 \text{Log}_{10}(D_{qi}) + \epsilon_i \quad (1)$$

where: N_i = trees per acre of stand i ,
 D_{qi} = quadratic mean diameter (in.) of stand i ,
 β_0, β_1 are parameters to be estimated, and
 ϵ_i is the random error associated with stand i , assumed $\text{NORM}(0, \sigma^2)$.

Following Avery and Burkhart (2001), a stand density index equation can then be created by requiring the equation to yield $\text{SDI} = N$ when $D_q = 10$ in. This is accomplished via the intercept term

$$\beta_0 = \text{Log}_{10}(\text{SDI}) + \beta_1 \quad (2)$$

Equation (2) can be substituted into equation (1), to yield the SDI equation of the form

$$\text{Log}_{10}(\text{SDI}) = \text{Log}_{10}(N_i) + \hat{\beta}_1 \text{Log}_{10}(D_{qi}) - \hat{\beta}_1 \quad (3)$$

The fitted slope from equation (1) is used to parameterize equation (3), which subsequently can be used to calculate SDI for a particular slash pine stand, as long as the stand's trees per acre and quadratic mean diameter are known.

Equation (1) can also be used to determine if the slope (self-thinning trajectory) is the same for both thinned and nonthinned slash pine stands by incorporating an indicator variable (I_i)

$$\text{Log}_{10}(N_i) = \beta_0 + (\beta_1 + \beta_2 I_i) \text{Log}_{10}(D_{qi}) + \epsilon_i \quad (4)$$

where: $I_i = 1$ if stand i has been thinned, 0 otherwise,
 β_2 is the parameter to be estimated, and
all other terms as previously described.

If β_2 statistically differs from 0 ($\alpha=0.05$) then the self-thinning trajectory varies between nonthinned and thinned stand status.

RESULTS AND DISCUSSION

The parameter estimates from fitting equation (1) to the nonthinned, thinned, and combined slash pine data sets, respectively, are shown in table 2. The slopes of all three fits, as evidenced by the p-values in table 2, were significantly different than 0 at $\alpha=0.05$. The approximate R^2 's reported in table 2 were obtained by transforming the predicted values of each fit into the original units of the Y-variable (trees per acre), thus expressing the proportion of variation in trees per acre explained by the independent variables (as opposed to the proportion of variation of Log_{10} [Trees per Acre] explained by the independent variables).

Table 1.—Summary statistics of the slash pine data

	n	Quadratic mean diameter (in.)		Trees per acre	
		Mean	Std. dev.	Mean	Std. dev.
Nonthinned stands	95	4.78	0.83	733.78	230.17
Thinned stands	1,543	9.31	2.23	186.90	95.51
Nonthinned and thinned stands combined	1,638	9.05	2.42	218.62	167.28

Table 2.—Parameter estimates from the fit of equation 1 to the nonthinned, thinned, and combined slash pine data sets

	Parameter	Estimate	Std. error	p-value	Approx. R ²	MAR ^a
Nonthinned data	β_0	3.71536	0.08836	<0.0001	0.5967	116.65
	β_1	-1.29634	0.13057	<0.0001		
Thinned data	β_0	4.13437	0.01704	<0.0001	0.8704	23.29
	β_1	-2.00530	0.01771	<0.0001		
Combined data	β_0	4.17800	0.01462	<0.0001	0.8913	29.91
	β_1	-2.04817	0.01542	<0.0001		

^aMAR is the mean absolute residual, the average of absolute values of the errors, expressed in trees per acre.

Figures 1 to 3 depict the fitted regression lines (eq. 1) to the nonthinned, thinned, and combined slash pine data sets, respectively. The slopes of the regression lines depicted in figures 1 to 3 and reported in table 2 are used in the SDI equation (eq. 3). The slope of the self-thinning trajectories of most species as reported by Reineke (1933) and Avery and Burkhardt (2001) is -1.605. The null hypotheses of t-tests of the form

$$H_0: \beta_1 = -1.605$$

$$H_1: \beta_1 \neq -1.605$$

were rejected at $\alpha=0.05$ for the slopes of all three model fits (p-value <0.03 in all cases) as expected. Recall, slash pine had been reported to depart from the self-thinning trajectory of other species.

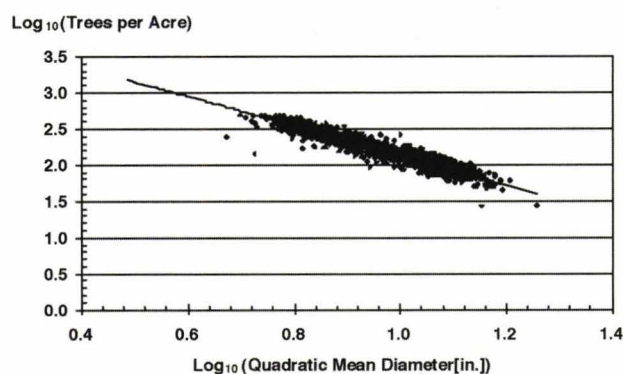


Figure 2.—Regression fit (line) obtained when fitting equation (1) to the thinned slash pine data (points).

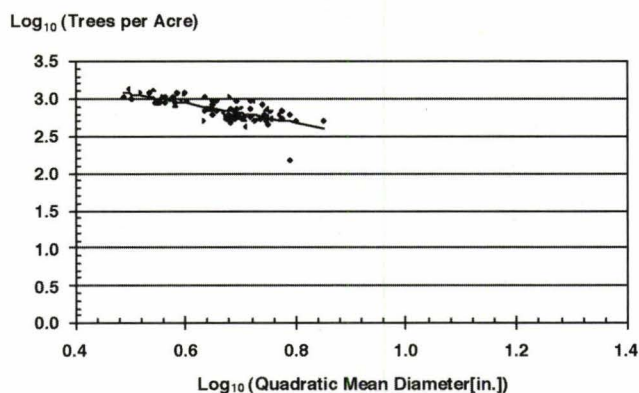


Figure 1.—Regression fit (line) obtained when fitting equation (1) to the nonthinned slash pine data (points).

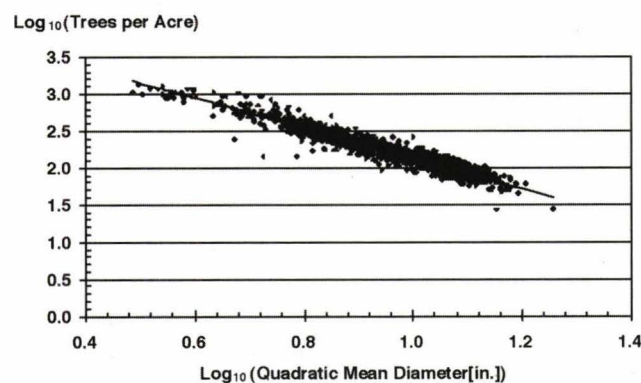


Figure 3.—Regression fit (line) obtained when fitting equation (1) to the combined slash pine data (points).

Table 3.—Parameter estimates from the fit of equation 4 to the combined slash pine data

	Parameter	Estimate	Std. error	p-value	Approx. R ²	MAR ^a
Combined data	β_0	4.10698	0.01707	<0.0001	0.8970	29.28
	β_1	-1.87117	0.01373	<0.0001		
	β_2	-0.10584	0.02752	<0.0001		

^aMAR is the mean absolute residual, the average of absolute values of the errors, expressed in trees per acre.

What was unexpected was the apparent difference in the self-thinning trajectories of the nonthinned and thinned slash pine stands. As a result, an indicator variable was introduced into equation (1) to test if the slopes were significantly different between the nonthinned and the thinned data (eq. 4). Parameter estimates from fitting equation (4) to the combined slash pine data set are shown in table 3.

The p-value for the test

$$H_0: \beta_2 = 0$$

$$H_1: \beta_2 \neq 0$$

was <0.0001; therefore, the slope is indeed statistically different between the nonthinned and the thinned slash pine stands. Perhaps this is the result of the management style of this particular landowner.

The landowner that provided the data employs thinning regimes; thus, older, nonthinned stands were not included in the data set. This may mean the nonthinned stands never reached the self-thinning threshold, possibly influencing the slope estimate from that portion of the data. More nonthinned slash pine data will need to be examined to address this issue.

The following SDI equation obtained by fitting equation (1) to the combined slash pine data set is thus cautiously recommended for use until the nonthinned slope can be further evaluated

$$\text{Log}_{10}(\text{SDI}) = \text{Log}_{10}(N_i) - 2.04817\text{Log}_{10}(D_{qi}) + 2.04817 \quad (5)$$

It is hoped that equation (5) will serve as the basis for continued research into SDI for slash pine and eventually lead to the creation of an SDI-based spreadsheet management tool for slash pine similar to the loblolly pine spreadsheet presented in Doruska and Nolen (1999).

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PICTURE #	LAST NAME	FIRST NAME	PICTURE #	LAST NAME	FIRST NAME
1	Boyack	Gary	33	Woodall	Chris
2	Kotar	John	34	Carr	Bill
3	Hokans	Rickard	35	Miettinen	Jukka
4	Breidt	Jay	36	Bragg	Don
5	Cieszewski	Chris	37	Laustsen	Kenneth
6	Dunham	Philip	38	Winterberger	Kenneth
7	Doruska	Paul	39	Helmer	Eileen
8	Sharma	Mahadev	40	Melson	Susanna
9	Hoppus	Mike	41	Van Deusen	Paul
10	Riemann	Rachel	42	Reams	Gregory
11	Bevilacqua	Eddie	43	Patterson	Paul
12	Zhang	Lianjun	44	Murray	Ronald
13	Scott	Charles	45	McRoberts	Ron
14	Lessard	Veronica	46	Fried	Jeremy
15	Heath	Linda	47	Edwards	Thomas
16	Jenkins	Jennifer	48	Butler	Brett
17	Meldahl	Ralph	49	Roller	Norm
18	Frescino	Tracy	50	Smith	Brad
19	Moisen	Gretchen	51	Brandeis	Tom
20	Zhou	Xiaoping	52	Lynch	Thomas
21	Smith	Erin	53	Finco	Mark
22	Moser	John	54	Caylor	Jule
23	Hansen	Mark	55	McCollum	Joe
24	Burk	Tom	56	Mullen	David
25	Malmquist	Andy	57	Mills	John
26	Gartner	David	58	Kelly	John
27	Roesch	Francis	59	Van Hees	Willem
28	Matney	Tom	60	Dunham	Paul
29	Schulz	Beth	61	Gillespie	Andy
30	Campbell	Sally	62	Hyink	David
31	Leary	Rolfe	63	Lister	Andrew
32	Iverson	Louis			

NOT PICTURED

LAST NAME	FIRST NAME
Alegria	Jim
Baldwin	Clark
Barrett	Tara
Bechtold	Bill
Chojnacky	David
Clutter	Mike
Cooke	Bill
Czaplewski	Ray
Devon	Hugh
Ek	Alan
Gallion	Joey
Goebel	Jeff
Goergen	Michael
Marzolo	Laurie
Opsomer	Jean
Prisley	Steve
Radcliffe	Samuel
Schwalm	Christopher
Shao	Guofan
Smith	William
Thiede	Gerald
Van Dyck	Michael
VanHooser	Dwane
Wackerman	Christopher
Williams	Michael
Wynne	Randy
Zakrzewski	Voyteck
Zweifler	Mark

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Documents contributions to forest inventory in the areas of sampling,
remote sensing, modeling, information management, and analysis with
emphasis on implementation of the annual inventory system of the
Forest Inventory and Analysis program of the USDA Forest Service.

KEY WORDS: annual forest inventory, estimation, sampling, imputa-
tion, modeling, remote sensing.

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